Nonintrusive Behavioral Sensing and Analytics for Supporting Human-Centered Building Energy Efficiency

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Abstract. Occupant behavior is a significant factor affecting building energy use and occupant comfort. Capturing occupant behavior, therefore, holds great promise toward human-centered building energy efficiency. However, existing methods for behavioral sensing and analytics are mainly based on intrusive sensing techniques (e.g., visual and acoustic sensing), which are known for infringing occupant privacy and have limited applicability. As such, the authors propose a novel nonintrusive approach for behavioral sensing and analytics. It uses (1) environmental chemical sensing to detect air composition changes caused by occupant behaviors, and (2) machine learning to learn from the air data to extract behavior information (e.g., occupancy and behavior type). This paper focuses on presenting the proposed approach and its evaluation in extracting occupancy information. The preliminary experimental results show that the proposed approach achieved an accuracy of 64.59% in sensing and analyzing occupancy, indicating the potential of the nonintrusive approach in supporting human-centered energy efficiency.

1. Introduction

Buildings represent a source of enormous untapped energy efficiency potential. In the past decade, building energy intensity (energy use per square meter) has declined at an annual rate of around 1% (International Energy Agency, 2020). Nevertheless, the full potential of building energy efficiency has not yet been achieved. As estimated by the Internal Energy Agency (IEA), building energy intensity in 2030 needs to be 45% less than that in 2020, in order to tap into the full efficiency potential to achieve the universal energy access goal by the United Nations (International Energy Agency, 2021). The development of building energy codes and advancement in high-efficiency energy technology have contributed to the improvement of building energy efficiency, but are not sufficient to harness its full potential. Buildings are complex sociotechnical systems with dynamic human-building interactions (Lumpkin et al., 2020). Because of the differences in the behaviors of building occupants, buildings often have significant variances in energy computation, even if they are designed under the same codes and equipped with the same energy technology (Van den Brom et al., 2019). Recent studies (e.g., Paone and Bacher, 2018; Jang and Kang, 2016; Rafsanjani and Ahn, 2016), thus, emphasize the importance of sensing and analyzing occupant behavior and incorporating the behavior into energy optimization for human-centered building energy efficiency to harness the untapped efficiency potential.

However, sensing and analyzing occupant behavior is challenging because of two primary reasons. First, occupant behavior is of high diversity. As people spend on average more than 90% of their time indoors (Al horr et al., 2016), the diverse types of human behavior that exist in the universe occur frequently in buildings. The behaviors of occupants in buildings include energy-use behaviors (e.g., adjusting thermostats, opening/closing windows, turning on/off lights, using electric appliances, etc.) and non-energy-use behaviors (e.g., leisure, office, and occupational behavior). Each high-level non-energy-use behavior has a multitude of sub-types. For example, leisure behavior includes reading, entertaining, cooking, etc. The diverse types of occupant behavior to be captured significantly challenge the capability of behavioral sensing systems. Second, occupant behavior is privacy-sensitive. Occupants generally do not prefer and

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even are against being directly monitored. Studies (e.g., Tomah et al., 2016) show that occupant privacy is one of the most significant concerns in the era of urbanization and digitalization. Protecting occupant privacy becomes even more important in buildings, because buildings are private environments where people live, work, and study on a day-to-day basis. Hence, while we attempt to deploy sensing and analytics techniques to monitor occupants and their behavior, we must protect their privacy.

To address these challenges, the authors propose a novel nonintrusive behavioral sensing and analytics approach for supporting human-centered building energy efficiency. The proposed approach leverages (1) environmental chemical sensing to detect air composition changes caused by different types of occupant behavior, without collecting sensitive private information from occupants, and (2) machine learning to learn from the air data to extract occupant behavior information (e.g., occupancy and behavior type). This paper, as a pilot study, focuses on presenting a proof-of-concept prototype developed to evaluate the feasibility of the proposed nonintrusive approach. The prototype includes two primary components: (1) a CO_2 sensor-based nonintrusive sensing system for collecting CO_2 concentration data, and (2) a bidirectional long short-term memory (bi-LSTM)-based information extraction model for extracting occupancy information from the collected concentration data.

2. State of the Art and Knowledge Gaps

A body of research efforts have been untaken to sense and analyze occupant behavior using various techniques, including wearable sensors, object sensors, and cameras. Despite the importance of these efforts, two primary knowledge gaps are identified. First, there is a lack of methods that can sense and analyze the large number of occupant behavior types that exist. Existing behavioral sensing methods mainly rely on sensing techniques that are specialized in sensing certain types of behaviors. For example, wearable sensors, in addition to their adherence problems (e.g., people stop using wearable sensors with time), mainly leverage accelerometers to capture behaviors with distinctive motion patterns, such as different phases of exercising (Walker et al., 2016). Object sensors, such as Wi-Fi, passive infrared (PIR) sensors, and smart meters, provide a limited amount of behavioral information. For instance, Wi-Fi mainly captures the locations of occupants to derive occupant behaviors (Ding et al., 2021). However, location information alone is not enough because different behaviors can occur at the same location. PIR sensors mainly capture the motion of occupants (Yan et al., 2018), but are not able to detect occupant behaviors that are relatively stationary. Smart meters mainly monitor the energy use of electronic devices to analyze occupant behaviors in close connections with such devices (e.g., working) and are, thus, limited in sensing and analyzing behaviors that do not involve the use of electronic devices (Razavi et al., 2019).

Second, there is a lack of methods for nonintrusive behavioral sensing and analytics. Occupants value their privacy, especially in indoor environments. As such, there is an evident need to conduct behavioral sensing and analytics in a nonintrusive manner to protect occupancy privacy. Visual sensing using cameras, compared to other sensing techniques such as those discussed above, is more capable of sensing different types of occupancy behavior. However, despite its advantages, visual sensing is often criticized for its privacy infringement issues, because it collects sensitive private information from occupants (e.g., facial features, body shape, etc.). Although there are privacy protection techniques (e.g., face blurring), people still feel uncomfortable under visual monitoring. For example, in many cases, people do not want to be monitored by video cameras even though they are informed that key visual features in the images frames of videos are anonymized, the images are 100% secure, and no other parties will have access to the images (Xu and Pombo, 2019).

3. Proposed Nonintrusive Behavioral Sensing and Analytics Approach

To address the aforementioned knowledge gaps, the authors propose a novel nonintrusive behavioral sensing and analytics approach. The proposed approach leverages (1) environmental chemical sensors to nonintrusively sense occupant behavior based on air composition changes caused by occupant presence and occupant behaviors, without collecting any sensitive and private personal information; and (2) machine learning to learn from the air composition data to analyze and extract information that describes occupancy and occupant behavior (both energy-use and non-energy-use behavior). To evaluate the feasibility of the proposed approach, this paper, as a pilot study, focuses on presenting a proof-of-concept prototype, which leverages CO_2 sensor-based nonintrusive sensing system and supervised deep learning for sensing and analyzing occupancy information. The prototype includes two primary components: nonintrusive behavioral sensing, and nonintrusive behavioral analytics.

3.1 Nonintrusive Behavioral Sensing

In this paper, the nonintrusive behavioral sensing was conducted using a CO_2 sensor-based sensing system. A CO_2 sensor was chosen and used in this pilot study because of three primary reasons. First, CO_2 sensors are economical and are already equipped in most buildings. Second, CO_2 sensors have a wide detection range, which allows for detecting CO_2 concentration changes in all directions of an indoor space. Third, more importantly, the sensors only collect CO_2 concentrations and do not collect any sensitive and private personal information from occupants (e.g., facial and body features). The development of the sensing system included two primary steps: sensing system design, and sensing system calibration.

Sensing System Design. The design of the proposed CO_2 sensor-based sensing system is depicted in Figure 1. The sensing system includes a breadboard, an analog-digital converter, a general-purpose input/output (GPIO) extension board, and a Raspberry Pi. The CO_2 sensor is a metal oxide semiconductor (MOS)-based sensor for collecting CO_2 concentrations in the hosting environment. It includes a variable resistor to respond to and sense different levels of CO_2 concentrations and a load resistor to control the sensitivity and accuracy of the sensor in responding to CO_2 concentration changes. The CO_2 concentrations collected by the sensor are in the form of analog signals, which are converted to digital signals by the analog-digital signal converter (a MCP 3008 chip in the design). The GPIO board transfers the digital signals into a machine-readable format and transmits the signals to a central processing unit (CPU) on the Raspberry Pi (which is a microcomputer with a graphic interface) for data storage.

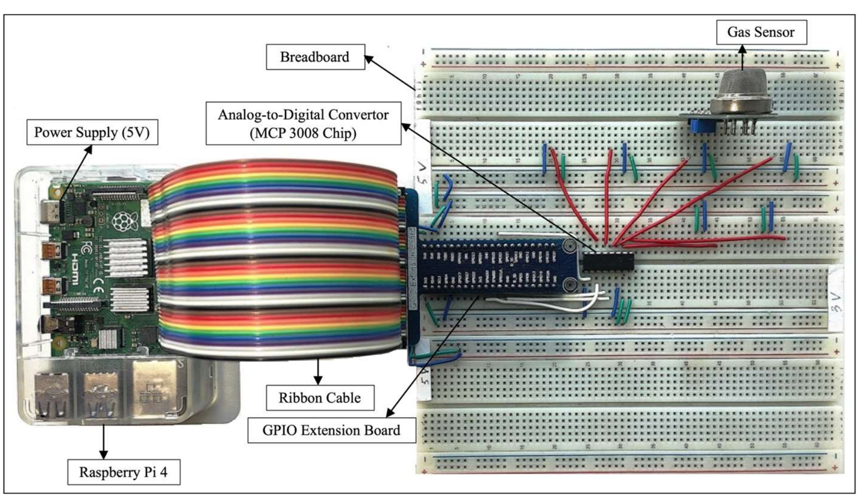

Figure 1: Design of Proposed Nonintrusive Sensing System.

Sensing System Calibration. The CO_2 sensor needs to be calibrated to establish a baseline CO_2 concentration in the clean air. Without the calibration, the sensor would use the CO_2 concentration level at the time of deploying the sensing system in the hosting environment as the baseline, which could result in improper sensing of CO_2 concentrations (e.g., concentrations that are lower than the concentration level at the deployment). The calibration aims to fix the resistance of the variable resistor to establish a resistance baseline according to the CO_2 concentration in the clean air. The sensor was calibrated by (1) pre-heating the sensor for 24 hours without any data collection, (2) placing the sensor in a clean air environment (i.e., in a natural landscape), and (3) monitoring the resistance value until it becomes fixed to complete the calibration process.

3.2 Nonintrusive Behavioral Analytics

Nonintrusive behavior analytics aims to learn from the data collected using environmental chemical sensors to extract occupant behavior information. This paper focuses on extracting occupancy information from CO_2 concentration data collected using the sensing system (as per Section 3.1). The analytics includes three components: outlier removal, data standardization, and deep learning.

Outlier Removal. Outlier removal was conducted to remove CO_2 concentration data instances that deviate significantly from the other instances in the dataset. Two sources of outliers were identified: sensor malfunctions caused by the fluctuations in the conditions of the hosting environment (e.g., drastic humidity and temperature changes), and sensor overreactions (e.g., a sudden surge in CO_2 concentrations caused by occupants directly exhaling to the sensor). Such outliers skew the distribution of the data and thus negatively affect the performance of the subsequent machine learning. As such, outliers were removed using the Pauta criterion (Li et al., 2016). The Pauta criterion was used because it is the standard outlier removal method for normally distributed data, such as the CO_2 concentration data in this study. As per Equation (1), a data instance is considered as an outlier and thus removed, if the residual error between the instance and the mean of all the instances is greater than 3σ. In Equation (1), X is arithmetic mean of all data instances in the dataset, X_b is a data instance, V_b is residual error, and σ is standard deviation of all data instances.

$$|V_b| = |X_b - X| > 3\sigma \tag{1}$$

Data Standardization. Data standardization was conducted to scale the data in a way that the scaled data can center around a mean of zero. Data standardization allows training more robust machine learning models and was, thus, conducted in this study. The standard score (also referred to as the z-score), which is a numerical measure that describes the relationship between a data instance and the mean of all the data instances, was chosen for the standardization. The CO_2 concentration data were standardized using Equation (2), where X is arithmetic mean of all data instances in the dataset, X_b is a data instance, σ is standard deviation of all data instances, and Z_b is the z-score of data instance X_b (which represents the standardized value for X_b).

$$Z_b = (X_b - X) / \sigma \tag{2}$$

Deep Learning. A deep learning architecture was developed to learn from the standardized CO_2 concentration data to extract occupancy information. It learns from CO_2 concentrations from past and the current time intervals to predict the occupancy at the current time interval. As shown in Figure 2, the architecture includes three layers: an input layer, a bi-directional long short-term memory (bi-LSTM) layer, and a softmax output layer.

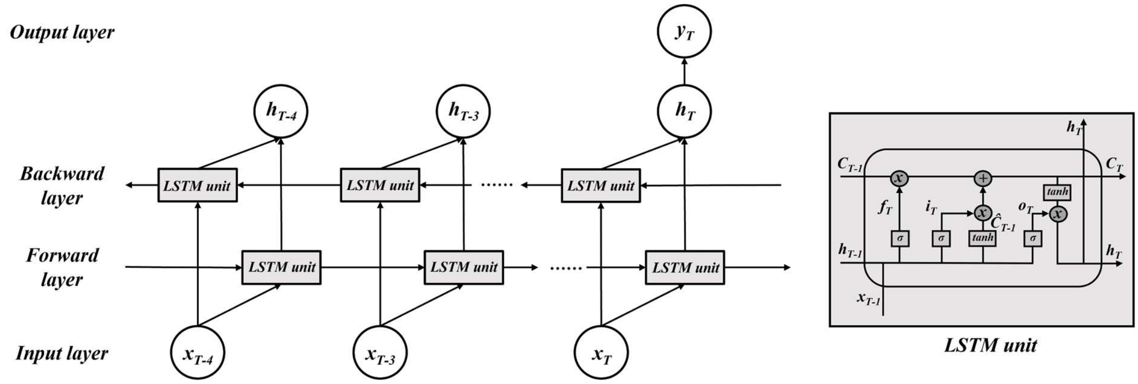

Figure 2: Learning Architecture for Extracting Occupancy Information from CO_2 Data.

The input layer takes vectors of CO_2 concentrations at consecutive time intervals as input, e.g., {*T-4, T-3, T-2, T-1, T*}. In this study, a vector includes CO_2 concentrations collected within a one-minute time interval. CO_2 concentrations from previous intervals were also used to extract the occupancy information at the current interval *T*, because this allows enriching the features used for the extraction and capturing the sequential and temporal changes in the concentrations to inform the extraction. The LSTM layer maps each input vector into a hidden representation in a way that the temporal dynamics connecting the data and the nonlinear dynamics of the data are captured by the hidden representation. LSTM is a special recurrent neural network that includes "gate" structures to regulate the flow of information in the network. As shown in Figure 2, LSTM includes three "gate" structures: a forget gate to decide which values of the previous state h_{T-1} and input x_{T-1} need to be preserved/remembered, an input gate to decide which values of the conveyor belt need to be preserved, and an output gate to decide what flows from the conveyor belt C_{T-1} to the state h_T. In this study, a bi-LSTM layer was used, because it allows for capturing the flow of information about CO_2 concentrations in both forward and backward directions to increase the amount of information (e.g., about temporal dynamics and nonlinearity) captured in the hidden representations for improved performance of occupancy information extraction. The output layer is a dense layer with the softmax activation function. The softmax function is a normalized exponential function to normalize the output of the learning architecture to a probability distribution over the desired output classes (i.e., occupancy categories in this study).

4. Nonintrusive Behavioral Sensing and Analytics Prototype Implementation

The behavioral sensing and analytics methods were implemented to develop a prototype system for evaluating the performance of the proposed nonintrusive approach. The implementation included four steps: (1) data collection, (2) dataset preparation, (3) algorithm implementation, and (4) performance evaluation.

Data Collection. The method presented in Section 3.1 was followed to develop a CO_2 sensor-based behavioral sensing system. The developed sensing system was instrumented in an office room for a week (from November 23 to November 30, 2021). The room, which is a fan-shaped room with a radius of 14.8ft and located on the campus of Stevens Institute of Technology, serves as an office for five graduate students. Figure 3 shows the raw CO_2 concertation data collected.

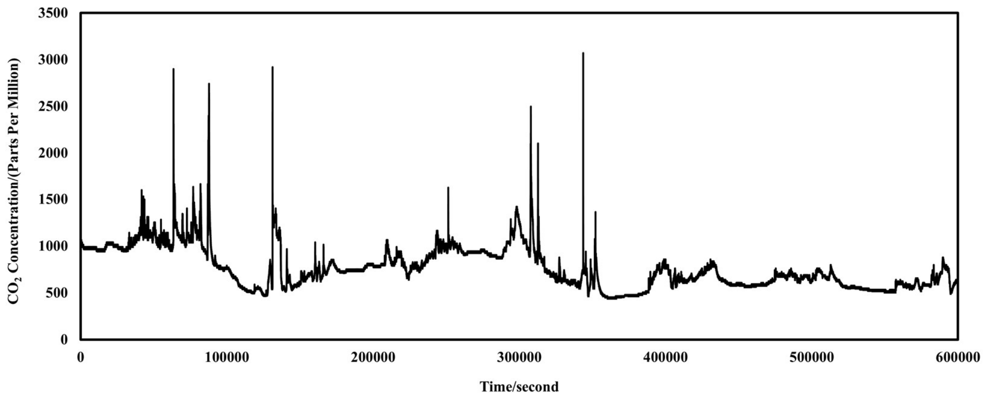

Figure 3: Collected Raw CO_2 Concentration Data.

Dataset Preparation. Dataset preparation included dataset creation and human annotation. To create the dataset, the raw time-series concentration data, as shown in Figure 3, were segmented into a set of non-overlapping intervals, where an interval has a width of one minute and includes a total of 30 concentration readings (sampling frequency = two seconds). A 'sliding window' approach with a timestep of five was then used to create individual inputs for the learning architecture. For example, to extract the occupancy information at time interval *T*, the input included the concentration readings in intervals *T-4*, *T-3*, *T-2*, *T-1*, and *T*. The input used to extract occupancy information at *T+1* included the readings at intervals at *T-3*, *T-2*, *T-1*, *T*, and *T+1*. Thus, the created dataset includes a total of 9,996 individual inputs. The dataset was randomly split into a training set and a testing set at a ratio of 7:3. Human annotation was conducted to mark-up the entire dataset with gold standard occupancy information. An office entrance and exit log was used to prepare the gold standard. The time of entrance and exit of an individual was manually recorded on the log, to count the gold standard occupancy for each time interval.

Algorithm Implementation. The nonintrusive behavioral analytics algorithm (as per Section 3.2) was implemented to train an occupancy information extraction model. The implementation was conducted using Keras (Keras, 2022), which is an open-source software library that provides a Python interface for artificial neural networks. The training included three steps. First, the hyperparameters for the learning algorithm were defined, as per Table 1. Second, the algorithm was initially trained for 1,000 epochs to identify the optimal number of epoch to avoid overfitting and underfiting. Based on the analysis of the relationship between training loss (categorical cross-entropy loss, as per Table 1) and trainng epoch number, the optimal epoch was identified as 700. As seen in Figure 4, the training loss after 700 epoches started become unstable, indicating model overfitting. Third, the algorithm was retrained using 700 epochs, resuling in a final extraction model.

Table 1: Hyperparameters of Nonintrusive Behavioral Analytics Algorithm.

Hyperparameter	Parameter Value
Batch size	32
Optimizer	Adam
Hidden representation/output layer dimension	250/6
Activation function of output layer	Softmax
Loss function	Categorical cross-entropy

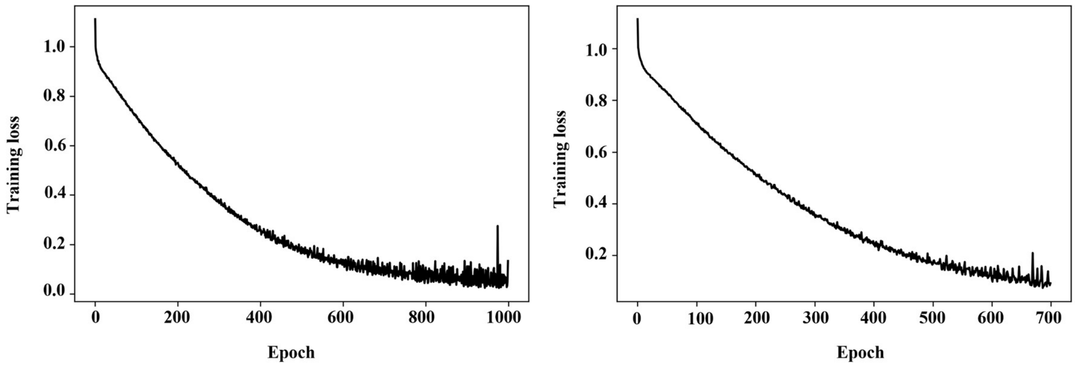

Figure 4: Training Loss against Training Epoch.

Performance Evaluation. The performance of the occupancy information extraction model was evaluated using four metrics: accuracy, precision, recall, and F-1 score. Accuracy, as per Equation (3), is the percentage of the number of correctly-extracted occupancy instances out of the number of all extracted occupancy instances. For each occupancy category: precision, as per Equation (4), is the percentage of the number of correctly-extracted occupancy instances out of the number of all extracted occupancy instances for the category; recall, as per Equation (5), is the percentage of the number of correctly-extracted occupancy instances out of the number of instances that should be extracted for the category; and F-1 score, as per Equation (6), is the harmonic mean of the precision and recall. In Equations (3-5), *TP* is true positive, *TN* is true negative, *FP* is false positive, and *FN* is false negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F\text{-}1\ score = \frac{2 \times (Recall \times Precision)}{(Recall + Precision)} \tag{6}$$

5. Preliminary Experimental Results and Discussion

Table 2 summarizes the performance results for sensing and analyzing occupancy using the proposed nonintrusive approach. Overall, using a CO_2 sensor-based sensing system and bi-LSTM, the proposed approach achieved an accuracy of 64.59% in extracting occupancy information. The preliminary results show the promise of the proposed approach in sensing and analyzing occupant behavior in a nonintrusive and hence more user-acceptable way.

Two main sources of errors were identified. First, from the sensing perspective, only one type of environmental chemical sensors, CO_2 sensor, was used in this pilot study. However, the results show that only using this single-type sensor is not sufficient for behavioral sensing and analytics (e.g., extracting occupancy information). As per Figure 5, the CO_2 data exhibit a high degree of with-in class variance. For example, when the gold standard occupancy category is "4", the CO_2 concentrations sometimes show consistent periodical changes around a standardized parts per million (PPM) of -0.25. In some other cases, for the same category, the CO_2 concentrations show drastic changes (e.g., surging abruptly to a standardized PPM of 0.75). Such a high degree of with-in class variances could be attributed to two reasons. On one hand, the sensing performance of environmental chemical sensors, such as the CO_2 sensor, can be affected by many factors in the hosting environment, such as ventilation, temperature, humidity, etc. For example, different humidity conditions may result in different sensor readings even when the occupancy remains the same. On the other hand, CO_2 concentrations alone are not fully indicative of occupancy. For instance, CO_2 may increase or decrease its concentration indoor due to window opening. In such cases, the collective patterns of multiple types of gases, such as CO and ethanol, may provide more discriminative information for machine learning to better extract occupancy information. As a result of such with-in class variances, some CO_2 concentration patterns that are different from other patterns used for model training but are for the same occupancy category were not captured and learned, which led to extraction errors. In their future work, the authors plan to incorporate additional sensors into the nonintrusive sensing system to capture the factors affecting the sensing performance (e.g., humidity, temperature, and lighting sensors) and other types of gases that are also indicative of occupancy and occupant behavior (e.g., ethanol, methane, and butane sensors).

Table 2: Performance Results for Nonintrusive Occupancy Sensing and Analytics.

		Gold Standard Occupancy						**Performance Result**			
		0	**1**	**2**	**3**	**4**	**5**	**Precision**	**Recall**	**F-1 score**	**Accuracy**
Extracted Occupancy	**0**	1,104	76	89	58	14	39	80.00%	82.95%	81.45%	64.59%
	1	53	115	79	28	2	7	40.49%	34.12%	37.04%	
	2	60	88	335	94	8	4	56.88%	55.10%	55.97%	
	3	58	49	95	328	18	15	58.26%	60.97%	59.58%	
	4	27	1	2	23	24	11	27.27%	30.77%	28.92%	
	5	29	8	8	7	12	31	32.63%	28.97%	30.69%	

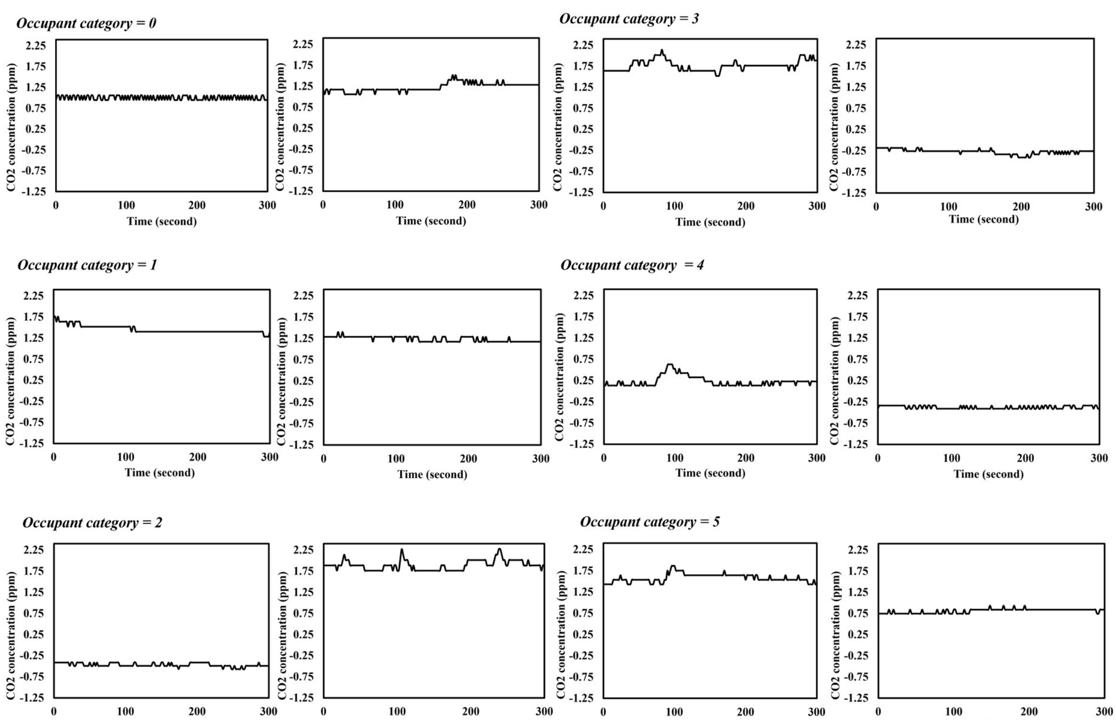

Figure 5: Examples of with-in Class Variances in CO_2 Concentration Data.

Second, from the machine learning perspective, the class imbalance and the ambiguity between adjacent occupancy categories also contributed the extraction errors. On one hand, as shown in Table 2, the occupancy categories/classes are naturally imbalanced. For example, the percentages of instances in occupancy categories “0” to “5” are 44.38%, 11.24%, 20.27%, 17.94%, 2.6%, 3.57%, respectively. Such class imbalance caused instances in the majority classes (e.g., occupancy categories “2” and “3”) get sufficiently learned at the cost of insufficiently learning from those in the minority classes (e.g., occupancy categories “4” and “5”). On the other hand, the ambiguity between adjacent occupancy categories posed challenges for the extraction model to correctly extract occupancy information. For example, as shown in Table 2, a total of 94 instances, which belong to category “3”, were incorrectly extracted into category “2”. One of the primary reasons for such ambiguity could be the similarity between CO_2 patterns in adjacent categories. For example, as shown in Figure 5, the ranges and patterns of CO_2 concentrations for categories “2” and “3” are highly similar. In their future work, in addition to leveraging more types of sensors in the sensing systems to address the ambiguity, the authors also plan to incorporate data balancing methods (e.g., cost-sensitive learning) in the proposed behavioral analytics to address the class imbalance problem.

6. Conclusions and Future Work

In this paper, the authors proposed a novel nonintrusive approach for occupant behavioral sensing and analytics to better support human-centered building energy efficiency. The significance of this paper lies in that the paper is among the first to investigate the use of environmental chemical sensors to sense and analyze occupant behaviors in a truly nonintrusive way. The proposed approach senses and analyzes air composition changes caused by occupancy and occupant behaviors to enable the extraction of occupant behavior information. Such a novel nonintrusive approach would allow for capturing diverse occupant behaviors while significantly mitigating the privacy concerns raised by building instrumentations. A prototype system, which includes a CO_2 sensor-based sensing system and a bi-LSTM-based occupancy information extraction model, was developed in this pilot study to evaluate the feasibility of the proposed nonintrusive approach. The prototype was implemented in sensing and analyzing CO_2 concentrations to extract occupancy information. The preliminary results show that the proposed approach achieved an accuracy of 64.59% in extracting occupancy information from CO_2 concentration data. The results show the potential of the proposed approach in better sensing and analyzing occupant behavior (including energy-use and non-energy-use behaviors) for human-centered energy efficiency.

In their future work, the authors plan to focus their research efforts on two main directions. First, incorporating multi-type environmental chemical sensors into the proposed nonintrusive sensing system to improve the capability of the behavioral sensing. Such sensors include sensors for sensing multiple types of gases (e.g., ethanol, ammonia, hydrogen sulfide, etc.) and sensors for sensing ambient conditions (e.g., temperature, relative humidity, etc.). Second, developing real-time, cost-sensitive machine learning methods that can extract information about occupancy and occupant behavior for multi-zone and multi-occupancy buildings in real time. This effort would offer opportunities for real-time, human-centered building operation and control to simultaneously maximize energy efficiency and improve occupant comforts.

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