IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-6, June 2019 E-ISSN: 2347-2693

Indirect Occupancy Detection using Environmental SensorData for Smart Office Buildings

C. Durai

Department of Computer Science, Kamarajar Government Arts College, Surandai, Trinelveli, Tamilnadu, India

*Corresponding Author: *duraidotnet@gmail.com*

DOI: https://doi.org/10.26438/ijcse/v7i6.10921095 | Available online at: www.ijcseonline.org

Accepted: 09/Jun/2019, Published: 30/Jun/2019

***Abstract*—**Buildings are one of the largest energy consumers around the world. Towards reducing the energy wastage in buildings, occupancy based control systems are becoming more wide-spread in commercial office buildings. Accurate identification of occupancy is crucial for such automated energy monitoring systems and for other potential applications such as personal comfort, air quality, and energy auditing. However, efficient and accurate ways to identifying occupancy in large scale buildings is a challenging task. Several approaches have been studied in literature ranging from direct to indirect approaches. In this paper, we present a nonintrusive and indirect occupancy detection approach using environmental sensor data as proxy. Specially, we used temperature and Carbon dioxide sensor dataset available in public domain. We employed the wide used k-means clustered algorithm for identifying occupied and unoccupied state (binary occupancy) of an office room. The proposed approach is validated on a public dataset with one week of environmental sensor data and results are analyzed using confusion matrix. Our experimental results show that the accuracy of detecting binary occupancy is 87.57%. We planned to extend our approach using other environmental sensor data.

***Keywords*—**Smart buildings, energy management, occupancy detection, data mining, and clustering

I. INTRODUCTION

Buildings are one of the largest energy consumers accounting for approximately one-third of total energy use worldwide [1]. It is expected energy demand continues to be increased at an alarming rate due to rapid urbanization and high growth in the building sector. There are several factors that influence the energy consumption of a building such as heating, ventilation, and air-conditioning (HVAC) systems, lighting systems, IT loads, among others. Moreover, building occupancy also influences the energy consumption of buildings due to the usage of diverse devices on their day-to-day usage [2]. Several efforts have been made to reduce the energy usage of the buildings such as energy auditing, benchmarking, retrofitting (changing older systems with new energy efficient systems such as LED lights), anomaly detection [3], and instrumenting automated energy monitoring systems for fine-grained energy management in the buildings.

Recent research has shown that occupancy based control systems can significantly reduce energy usage in the order of 30% to 42% [4] [5]. For example, occupancy-based lighting and HVAC control system, together with schedules, can automatically turn off the devices when a building region is unoccupied, resulting in reduced energy wastage. For all these systems to be effective, accurate occupancy information is required. Further, occupancy information is also vital for securing the buildings.

Several occupancy detection methods have been proposed in literature. They can be broadly categorized into direct and indirect sensing methods [6] [7]. Direct sensing approaches use sensing systems that directly monitors the building occupants. An example of direct sensing is using Passive Infrared (PIR) motion sensor [8] [9], or cameras [10] [11]. Whereas, indirect sensing approaches leverage the sensors that don't directly monitor the occupants but having information about occupancy. An example of indirect sensing is using CO2 sensors as a proxy for measuring occupancy [12] [13].

In both the cases, the measured occupancy information can be at different granularity (presence, count, identify, activity, and behavior), temporal (real-time, minutely, hourly, daily, etc.), and spatial resolution (room, region, floor, and whole building), tailoring to the needs of the specific energy management application. For example, mere presence information is sufficient for an occupancy-based lighting system, whereas, the count of occupants would be required by the occupancy based HVAC control system. Further, there are several merits and demerits (intrusive, privacy, cost, accuracy, latency, computation, etc.) while using a particular occupancy detection method, and as such, no single method seems to be suitable for meeting the requirements of all building management applications.

In this paper, we present an indirect occupancy sensing method for detecting the occupant's presence in an office room of a commercial building. Specifically, it is a binary occupancy detection method which is limited to identifying whether someone is present (yes) or not (no) in the office room. Since direct sensing methods incur additional cost for deployment of sensors, we employed an indirect sensing method using CO2 and temperature sensor data which is readily accessible from building management systems (BMS) in large-scale of commercial buildings for thermal comfort.

We model the binary occupancy detection problem as a clustering problem as there are only two states (occupied and not occupied) involved. To be more specific, we used k-means clustering algorithm for differentiating occupied intervals from not-occupied in an office room. Our experimental results, using a public dataset with about 8000 samples spanning over 7 days, show that the proposed clustering method achieves an accuracy of 87%. In the future, we plan to extend our approach using other clustering algorithms and other sensor data such as light, humidity and temporal features.

Rest of the paper is organized as follows. Section II contains the related work of occupancy detection methods for smart building applications. Section III contains dataset details and proposed methodology for indirect occupancy sensing using environmental sensors. Section IV describes the results and analysis followed by Section V concludes research work with future directions.

II. RELATED WORK

Several sensing modalities have been used in literature for occupancy detection. Their advantages and disadvantages are summarized. Passive Infrared (PIR) based motion sensors have been widely used for detecting binary occupancy [6] [7]. It is inexpensive, energy efficient, and non-intrusive. However, PIR sensors have several limitations, including a) they require a direct line of sight of occupants or a fixed view angle; b) they are highly sensitive to other ambient motions in the room such as the presence of ceiling fan, pets, etc.; c) they cannot detect when the occupants are in static position; and d) PIR sensors cannot be used for counting occupants. Due to these reasons, they often result in false triggers because of their high sensitivity. To address these problems, PIR sensors are often combined with door status sensors and shown to give better accuracy in occupancy detection and counting [7].

Vision-based systems (e.g., digital camera networks) also have been used in literature for occupancy sensing [10] [11]. Various image processing methods are applied over the captured video streams for occupancy detection and activity analysis. While the video feeds contain very rich information about occupants, including behavioral information, they raise privacy concerns. Hence they have very limited applicability to be deployed in all spaces [11]. Thermal cameras are relatively less sensitive to occupant's privacy concerns as they capture only the thermal profiles of the space. Combined with a PIR sensor, thermal cameras have shown to give much better accuracy in detecting occupancy in extreme conditions [14]. Other widely used sensors include Radio Frequency Identification (RFID) tags [15], sound sensors [16], but they also share similar limitations with vision-based systems.

In recent years, environmental sensors have also been used for indirectly measuring the occupied status of the buildings [13]. The widely used environmental sensors include air temperature, humidity, Carbon dioxide (CO2) concentration, and light intensity. These sensors are sensitive enough to capture the thermal energy and CO2 generated by humans, thus indirectly measures human occupancy. The primary advantages of environmental sensors are, a) they are already in operation in most of the buildings as part of the building management systems or home automation systems, b) they are nonintrusive and raises no privacy concerns, and c) they are economical and highly scalable as they eliminate the cost for sensor deployment and management. However, environmental sensors are less sensitive to occupants and they need some time for build-up. Advanced machine learning methods are used to model the relationship between the environment sensor's build-up rate and human occupancy [17].

III. DATASET

Due to practical difficulties in collecting the actual sensor data from BMS systems, we experimented our clustering based binary occupancy detection method on a public dataset. We used the occupancy detection dataset from the UCI machine learning repository[1]. This open dataset has one training and two testing datasets. There are 8143 samples, spanning over seven days, with environmental sensor readings from temperature, CO2, light intensity, and humidity sensors. This dataset also contains ground truth information about actual occupancy state of the office room, which was collected using pictures every minute.

Table 1: Properties of the dataset used in the proposed indirect occupancy sensing method

Dataset properties (training)	Value
Name of the sensor data used	Temperature and CO2
Time interval	1 min (1 week data)
Total number of samples	8,143
Number of occupied states	1,729

Number of unoccupied states	6,414
Percentage of occupied states	21.23 %
Percentage of unoccupied states	78.77 %

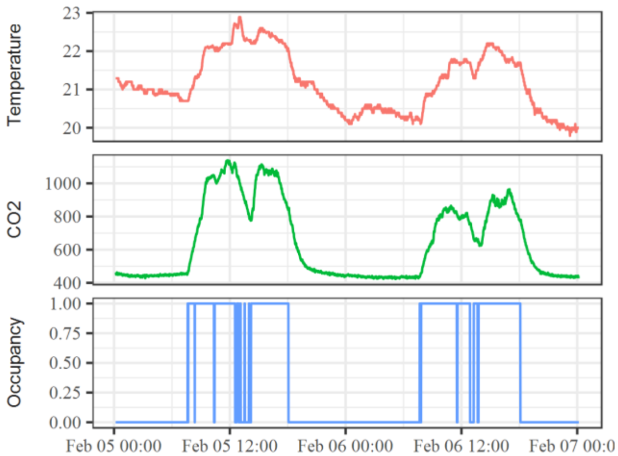

Figure 1: Sensor data readings for two day with ground truth occupancy information

The summary of the dataset is given in Table 1. In this work, we specifically used only the temperate and CO2 readings as these readings are readily accessible from BMS in real buildings. A sample of the sensor data points for two days are shown in Figure 1. We also studied the feasibility of using temperature and CO2 sensor readings as a measure to detect the occupied state of the office room. The pairs plot in Figure 2, shows that there is a clear separation of points between occupied and not occupied state, though there are some overlapping data points.

IV. METHODOLOGY

In this section, we explain the proposed indirect occupancy sensing approach using environmental sensor data. Moreover, we also describe the list of performance metrics used for measure the performance of the proposed occupancy detection method.

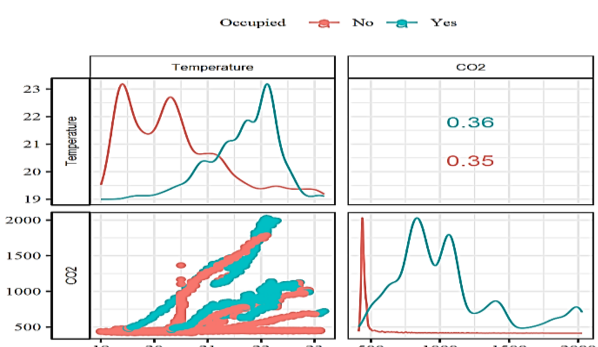

Figure 2: Pairs plot of temperature and CO2 sensor data points show a clear separation between occupied and unoccupied state of the office room.

A. Binary Occupancy Detection Methodology

As mentioned earlier, we model the binary occupancy detection problem as a clustering problem. Our objective is grouping the sensor data points into two clusters, one representing the occupied state and another representing the unoccupied state of the office room. We used the well-known k-means [18] clustering algorithm. The steps involved for binary occupancy sensing using k-means clustering is shown in Algorithm 1. Since the range of the values of temperature and CO2 sensors are different, and as a standard practice, we applied z-score normalization to bring them to the same range, before applying the k-means clustering algorithm. The transformed z-score values represent the distance between the original data and sample mean as a unit of the standard deviation of the sample. Since we already know there are only two states, we used k = 2 to cluster the data points.

B. Performance metrics

After clustering the sensor data readings into two groups, we count the number of data points or time intervals was correctly classified as occupied and unoccupied using the available ground truth data. We use the following two standard performance metrics, namely confusion matrix and accuracy, for measuring the effectiveness of the k-means clustering algorithm for binary occupancy detection method.

1. *Confusion matrix:* It is a two rows by two columns matrix that tabulates the number of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN)
2. *Accuracy:*Accuracy of the binary clustering is defined as below

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Algorithm 1: Binary occupancy detection method using *K-means clustering algorithm*

1. Create two starting centroids randomly for occupied and unoccupied state
2. While any point has changed cluster assignment
    a) for every point in our dataset:
        i. for every centroid:
           calculate the distance between the centroid and point
        ii. assign the point to the cluster with the lowest distance
    b) for every cluster calculate the mean of the points in that cluster
        i. assign the centroid to the mean

Table 2: Confusion matrix shows the difference between number of actual and predicted occupancy states in the input dataset

		Actual	
		Unoccupied	Occupied
Predicted	Unoccupied	5622	792
	Occupied	220	1509

V. RESULTS

After applying the k-means algorithm (k=2) over the input dataset, we compared the clustering results, that is the number of correctly identified occupied and unoccupied states, with the available actual ground truth data. We tabulated the results in a confusion matrix and calculated the accuracy of the model. The confusion matrix is shown in Table 2. The calculated accuracy is 87.57%. This accuracy can further be improved by including other environmental sensor data such as humidity and light intensity that we leave it as future work.

VI. CONCLUSION AND FUTURE WORK

Accurate identification of occupancy information is essential for several modern energy management applications such as occupancy-based lighting and HVAC control. In this work, we presented an indirect occupancy detection method using environmental sensor data as a proxy. We employed the widely used k-means clustering method for separating the occupied state of the room from the unoccupied state. Experiments were conducted on a public domain dataset and the results were analysed. The proposed method using only temperature and CO2 sensor data, that are already available in most of the commercial building's HVAC systems, achieves a prediction of 87.57%. We further plan to extend our approach using additional environmental sensor data.

REFERENCES

[1] IEA, World Energy Outlook, IEA Publications, Paris, 2013, pp. 2013

[2] S. D'Oca, T. Hong, and J. Langevin, "The human dimensions of energy use in buildings: A review" Renewable and Sustainable Energy Reviews, vol. 81, pp. 731–742, 2018.

[3] Rashid, H., Arjunan, P., Singh, P. and Singh, A., 2016, June. Collect, compare, and score: a generic data-driven anomaly detection method for buildings. In Proceedings of the Seventh International Conference on Future Energy Systems Poster Sessions (p. 12). ACM.

[4] V. Garg, N. K., Bansal, Smart occupancy sensors to reduce energy consumption. Energy and Buildings, 2000, 32(1):81-87.

[5] J. Brooks, S. Goyal, R. Subramany, Y. Lin, T. Middelkoop, L. Arpan, L. Carloni, P. Barooah, An experimental investigation of occupancy-based energy-efficient control of commercial building indoor climate, in: Proceeding of the IEEE 53rd Annual Conference on, IEEE, Decision and Control (CDC), Los Angeles, CA, 2014, pp. 5680–5685.

[6] Chen, Zhenghua, Chaoyang Jiang, and Lihua Xie. "Building occupancy estimation and detection: A review." Energy and Buildings (2018).

[7] Jung, Wooyoung, and Farrokh Jazizadeh. "Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions." Applied Energy 239 (2019): 1471-1508.

[8] Duarte C, Van Den Wymelenberg K, Rieger C. Revealing occupancy patterns in an office building through the use of occupancy sensor data. Energy and Buildings 2013;67:587–95.

[9] Agarwal Y, Balaji B, Gupta R, Lyles J, Wei M, Weng T. Occupancy-driven energy management for smart building automation. Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building. ACM; 2010.

[10] Kamthe A, Jiang L, Dudys M, Cerpa A. SCOPES: Smart cameras object position estimation system. Proceedings of the 6th European conference on wireless sensor networks. Cork, Ireland: Springer Verlag; 2009. p. 279–95.

[11] Y. Benezeth, H. Laurent, B. Emile, C. Rosenberger, Towards a sensor for detecting human presence and characterizing activity, Energy Build. 43 (2) (2011) 305–314.

[12] M. Jin, N. Bekiaris-Liberis, K. Weekly, C. Spanos, A. Bayen, Sensing by proxy: Occupancy detection based on indoor CO2 concentration, UBICOMM 2015, 2015, 14.

[13] L.M. Candanedo, V. Feldheim, Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models, Energy and Buildings, 2016, 112:28-39.

[14] A. Beltran, V.L. Erickson, A.E. Cerpa, Thermosense: occupancy thermal based sensing for hvac control, in: Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings, ACM, Rome, Italy, 2013, pp. 11:11–11:18.

[15] N. Li, G. Calis, B. Becerik-Gerber, Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations, Automat. Construct. 24 (2012) 89–99.

[16] E. Hailemariam, R. Goldstein, R. Attar, A. Khan, Real-time occupancy detection using decision trees with multiple sensor types, in: Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International, San Diego, CA, 2011, pp. 141–148.

[17] Z. Yang, N. Li, B. Becerik-Gerber, M. Orosz, A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations, in: Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International, San Diego, CA, USA, 2012, pp. 49–56.

[18] Jain, Anil K. "Data clustering: 50 years beyond K-means." Pattern recognition letters 31, no. 8 (2010): 651-666.

Authors Profile

Mr. C. Durai pursued his Bachelor of Science in Computer Science from Bharathidasan University, Trichirappalli, Tamilnadu, India and Master of Science in Computer Science from Manonmaniam Sundaranar University, Tirunelveli, Tamilnadu, India. He also pursued his Master of Philosophy in Computer Science from Annamalai University, Chithambaram, Tamilnadu, India and Master of Technology in Computer Science from Manonmaniam Sundaranar University, Tirunelveli,Tamilnadu, India. He is currently working as a lecturer in the Department of Computer Science, Kamarajar Government Arts College, Surandai, Tamilnadu, India. He has more than 8 years of teaching experience in teaching various computer science subjects. His main research work focuses on applied data mining techniques and time series analysis for smart buildings and energy sustainability.

