Real-time building energy and comfort parameter data collection using mobile indoor robots

Bharadwaj R. K. Mantha[a], Chen Feng[a], Carol C. Menassa[a], and Vineet R. Kamat[a]

[a]Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, USA.
E-mail: baddu@umich.edu, cforrest@umich.edu, menassa@umich.edu, vkamat@umich.edu

ABSTRACT

Optimizing and improving energy performance of buildings while maintaining occupants' comfort are primary goals for building managers. In order to analyze a building's energy performance and make informed retrofit, maintenance, or operational decisions, decision-makers need access to credible real-time data illustrating how building systems are being used by its occupants at a floor and room level granularity. Traditionally, such data has been collected in buildings using wired or wireless systems by installing a dense array of sensors in every building location that needs monitoring. This is an effort and cost-prohibitive approach, especially in existing older buildings where instrumentation and integration with existing building systems is challenging. This paper introduces a novel concept of using autonomous mobile indoor robots for monitoring various occupant comfort and energy parameters inside an existing building, and discusses how the collected data can be utilized in various analyses. The research evaluates the hypothesis that a single multi-sensor fused robotic data mule that collects building energy systems performance and occupancy comfort data at sparse locations inside a building can provide decision-makers with a rich data set that is comparable in fidelity to data obtained from pre-installed and fixed sensor systems. In order to demonstrate the effectiveness of the proposed approach, an experiment was conducted using a tele-operated robot outfitted with thermal comfort data collection sensors and a localization camera in a multi-occupancy space within a large university building. The data collected by the mobile robot was statistically compared with data obtained from the building's pre-installed Building Automation System. Experimental results demonstrated the proposed method's promise and applicability in collecting dense actionable data in large spaces using only a sparse set of sensors mounted on mobile indoor robots.

Keywords –

Mobile indoor robots, occupant comfort, data collection, and building energy monitoring.

1 Introduction

Buildings account for about 40% of the total energy consumption in US [1] with 80% of the total energy consumption occurring during the operation and maintenance phase of the facility [2]. Thus, optimizing and improving the energy performance of buildings and at the same time maintaining the occupants' comfort are some of the major areas of concern for building managers and stakeholders. In order to properly analyze the building's energy performance and make informed retrofit and/or maintenance and operations decisions, decision makers need access to credible data illustrating how the building systems (i.e., lighting and HVAC: Heating Ventilating and Air Conditioning) are being used by its occupants [3]. There is thus a tangible need to collect room and floor level data from buildings.

Existing building energy and occupant comfort data collection methods consist of a plethora of wireless sensors as part of a building automation system. However, there are lot of issues with these methods (i.e., significant upfront investment, complex installation integration process of large number of sensors, skilled manpower requirement, highly time consuming installation, maintenance, and calibration process) in implementing this approach especially in existing buildings (without the Building Automation System (BAS)). In an effort to mitigate these issues, the primary objective of this paper is to introduce a novel concept of using autonomous mobile indoor robots for monitoring various occupant comfort and energy parameters inside a building and discuss in detail how the data collected in the process can be utilized in various analyses. In addition, the advantages of this method over the existing state of the art methods are discussed. The proposed approach is validated through an experiment that was conducted in an academic building with a tele-operated mobile robot collecting the aforementioned data and the results were compared with data logged by an existing Building Automation System (BAS).

2 Background

Over the last few decades, intensive research has been carried out on autonomous indoor robots. Some of the critical components that govern the autonomous behavior of robots in an indoor environment are robotic mapping (constructing a map of the environment), localization (robot localizing itself in the map), pose estimation (the combination of pose and orientation of the robot in the current location), path planning (shortest or optimal path between its current location and next location), and obstacle avoidance (collision avoidance with humans or objects in the robot's path). Localization is one of the primary and important tasks that caught the attention of many researchers. Traditionally, non-visual-sensor-based networks were used such as Global Positioning System (GPS) [4], Inertial Measurement Unit (IMU) [5], Radio Frequency Identification (RFID) [6,7], Wireless Local Area Network (WLAN) [8, 9], Ultra-Wide Band (UWB) [10], Global Systems for Mobile communication (GSM) [11], Bluetooth [12], ZigBee (IEEE 802.15.4), Ultrasound and Infrared. Most of the aforementioned techniques either suffer from accuracy problems and/or require complex instrumentation of the monitored space. Rapidly growing computing capabilities and advancements in cheap and robust sensor technology, lead to vision based systems such as, Simultaneous Localization and Mapping (SLAM) [13] and Visual Registration [14], utilizing visual sensors such as camera and LIght Detection and Ranging (LIDAR). Though SLAM and UWB positioning systems are accurate, they suffer from factors such as accumulated errors [15], inability to adapt to environmental conditions, and requirement of an accurate signal propagation model [16]. On the other hand, fiducial markers developed by [14] have the potential to accurately localize the robot's position in an indoor environment (i.e., building floor level and room location), and are also cheap and easy to install [17].

This research uses fiducial markers as a cheap, accurate and easy to deploy indoor localization method with relatively low computing requirements [14, 18] for the purpose of collecting a dense building thermal comfort data set. This is in contrast to the traditionally used localization techniques such as dead reckoning (estimating the current position based on previous position, speed and elapsed time), SLAM, combination of sensors such as geometry sensors, angle measurement sensors, and range sensors that have limitations such as cost, accuracy and high computing capability requirements.

Previous examples of the applications of the indoor robots include health care services, domestic automation [19], intelligently programmable physical spaces for work life (The Robot Rooms) [20], hotel service robots [21], assistive robotic micro-rooms for the elderly [22] and many more. None of the above applications has, however, considered the potential use of robots to collect indoor building energy use and comfort parameter in an efficient and economical manner.

3 Importance of the Research

World energy use is rapidly increasing and so is the total energy use in buildings. The increase in energy demand has many environmental impacts such as resource depletion, climate change and ecological systems degradation [23]. Hence, energy efficiency measures have become increasingly important and significant research is being conducted in this area. In addition, literature also suggests that, by maintaining proper indoor environmental quality, occupant comfort, health and productivity can be significantly improved while ensuring that building consumes energy in the most efficient manner [24]. Thus, in the current scenario, occupant comfort and energy efficiency are the two primary goals of a building manager during the operation phase of any building.

Buildings are typically designed based on certain design assumptions which are inputted for the building energy simulation models. Buildings can be energy efficient, if operated and maintained as per the assumptions considered during the design phase. However, the actual conditions during the operation of the buildings always differ from the design assumptions considered, primarily owing to occupants' actions [25, 26, 27, and 28]. Generally, computer simulations and energy models are used for designing and predicting the performance of complex building systems. However, these energy models are generally not used during the operation phase of buildings. With the emerging ability to seed these models with real time data, these models can have several applications such as operation decision, monitoring based commissioning, energy policy framework, building energy audit, and building retrofit analysis. The state of the art technology proposes the use of real-time data for better prediction capabilities and improved analysis through Dynamic Data-Driven Simulation and Analysis (DDDSA). Although DDDSA models have the potential to significantly improve building performance, they require significant amount of high fidelity data [29].

The state of the art in both building energy and comfort parameters data collection in buildings is to use wired/wireless systems and instrument the building with several sensors (at least one set of sensors for every metric and location that needs to be monitored). These wireless or wired systems along with some actuators and control networks are the main components of BAS. Some of the many sensors that are required at every location are indoor and outdoor air temperature, indoor and outdoor humidity, CO_2 (for measuring indoor air-quality), occupancy (to detect if the space is being occupied), light (for measuring the indoor light levels), plug-load (for calculating the electricity consumption), and sound (to determine noise levels). The adoption of BAS is becoming more main stream in new commercial buildings, supported by building certification requirements and design provisions. However, this type of automation and dense network of sensors is not possible in existing old buildings because it involves significant amount of time, money, resources; in addition, to the potential complexity that might arise from integrating a dense sensor network with the existing building systems.

In contrast, the objective of this research is to develop and validate the hypothesis that a single multi-sensor fused robotic data mule, which collects comfort building energy, and occupancy data at every location by autonomously navigating the indoor built environment and can provide building decision makers with a rich data set. In addition, the goal is also to eliminate the need for a dense sensor network (which is required by the traditional data collection methods as discussed) while still obtaining data at same fidelity level. To validate the effectiveness of the data collected during such a process, an experiment was carried out using a tele-operated robot outfitted with a thermal comfort data collection sensors and a camera to assist in the navigation and localization of the robot within the space considered. Using robotic data mule, data was collected over a period of seventeen days in a multi occupancy space. This data was then compared with data obtained from the building's BAS. The design of the robot, entire experimental process and the results obtained are discussed in detail in the following sections of the paper.

4 Technical Approach

One of the main contributions of this paper is the design of the robot and the respective algorithms which are basis for the robots navigation in an indoor building environment and thermal comfort data collection. Some of the crucial aspects in the design of the robot are determining the type of data that needs to be collected (accordingly the type of sensors to be placed on the data mule), frequency of data collection (how frequently the data needs to be collected at every location), waiting time at each location of data collection, algorithms that will help decide the number of data mules required to monitor (depending on the size of the buildings) the entire building, optimizing the travel time and path. After the robot is designed, it needs to be tested and validated to check the effectiveness of the design and improvisations would follow accordingly. Hence, the technical approach is divided into two sections as follows: 1) Design of the robot and 2) Experimental Test-bed.

4.1 Design of the robotic data mule

After careful consideration of various parameters, a TurtleBot robot, equipped with the iCreate base was chosen as the mobile data collection platform and sensors such as Cozir® CM 0199 (for temperature, humidity, and CO_2 levels), HOBO U12 (for light and occupancy levels), Lutron (for natural light levels), NinjaBlocks (for air speed), Smart meters (for electricity consumption) was used for the data collection. Figure 1 shows the robot with the following components 1) TurtleBot – For navigating the indoor environment; 2) On-board netbook – To communicate with the TurtleBot; 3) RGB Camera - For the TurtleBot to localize itself in the indoor environment; 4) Remote laptop - For tele-operating the TurtleBot); 5) Sensors – For monitoring and data collection of various occupancy comfort (as shown in Table 1) and building energy parameters as discussed before. The following section provides a detailed description of the entire experimental setup and process.

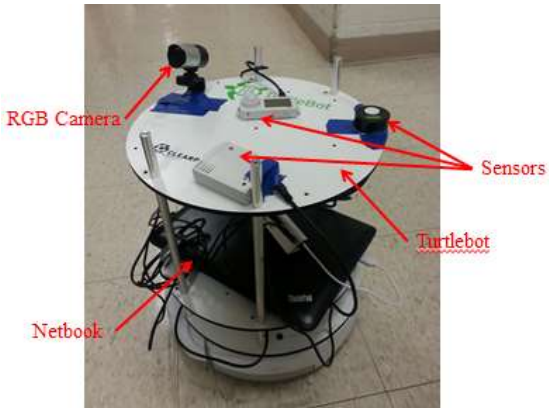

Figure 1: Figure showing all the components of robotic data mule used for occupant comfort and building energy monitoring data collection

4.2 Experimental Test-bed

The experiments conducted in the first phase of the research are to compare and demonstrate that the data gathered with the help of robotic data mule and the data collected using existing BAS are similar (both in quality and reliability) in terms of serving as input for subsequent analyses. Data mule gathered data regarding several aforementioned comfort parameters such as temperature, humidity, light, CO_2, and Occupancy. For the purpose of this paper, data comparison and validation is done only for temperature data, which plays a crucial role in determining the thermal comfort of the occupant and also has a direct impact on the energy consumption of the HVAC systems in buildings [31,32]. Experiments were conducted in the Ross

School of Business at the University of Michigan - Ann Arbor campus. The selected building is equipped with a BAS that collects different types of data at the room, system, and the building level. For example, different types of data gathered by the BAS of Ross are Control temperature, supply air damper point, room temperature, hot water valve pint, damper status operation, and damper status operation. The basement floor comprising of an open study lounge (monitored by one thermostat) and two group study rooms (each monitored by one thermostat) were chosen as the test bed for the experiments. Figure 2 shows the locations of the thermostats and/or the locations in the basement where the temperature readings were recorded by the BAS.

Table 1: Factors affecting occupants comfort in an indoor environment

Category	Description	Units	Reference
Thermal comfort	Input air temp (AHU)	°C	[30]
	Return air temp (From room/ hall)	°C	[30]
	CO_2	ppm	[30]
	Ventilation	cfm/ person	[26]
	Indoor Temperature	°C	[31,32]
	Ventilation type and Air Flow	-	[31]
	Heat Loss Coefficient	-	[32]
	Floor Area	m2	[31]
	Air Velocity (Indoor)	m/s	[31]
	Humidity (Indoor)	%	[31]
	Mean Radiant Temperature (MRT)	°C	[26]
Visual comfort	Lighting	Lux	[33,34]
Acoustic comfort	Noise/Sound levels	dB	[35]
Thermal, Visual, and Acoustic	Personal control over blinds, windows, and HVAC system.	-	[36,37, 38]
External/ Outdoor Factors	Wind Speed (Outdoor)	m/s	[39]
	Wind Direction (Outdoor)	°	[39]
	Outdoor Temperature	°C	[31]
	Humidity (outdoor)	%	[31]
	Solar Radiation	W/m^2	[39]

5 Research Methodology

In this section, the experimental procedure implementing the proposed idea to use autonomous indoor robots for building energy and comfort parameter data collection is discussed. The entire experimental process can be divided into the following steps, a) the robot has to localize itself in the indoor environment, b) navigate to the intended data collection locations, c) collect the respective data, and d) geo-tag and record the sensor data collected. Figure 3 shows the flowchart of the aforementioned sequential steps involved in the data collection process.

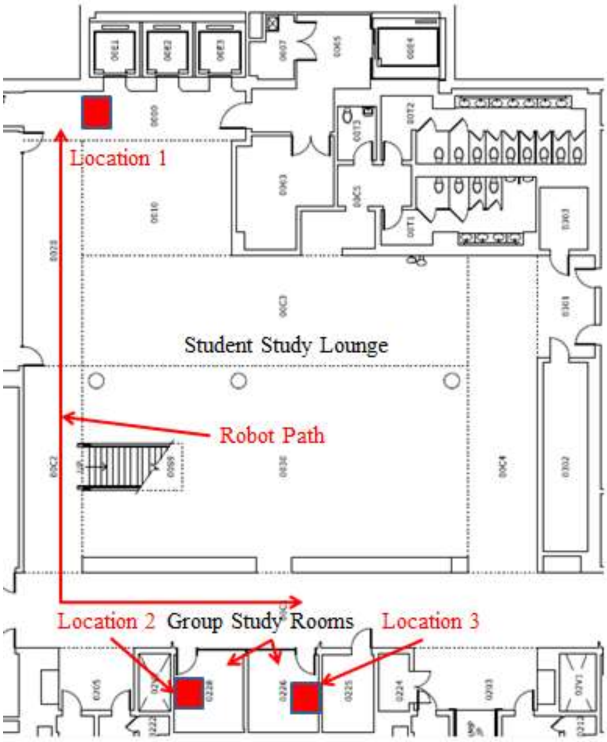

Figure 2: Basement floor plan of Ross School of Business. Rectangular points marked on the plan represent the locations where the data was collected.

5.1 Localization

For the localization of the robot, fiducial markers as shown in the Figure 4 were used at every location next to the thermostat. With the help of the on board RGB camera, an image of the marker is captured. Now, using the marker recognition module (an algorithm which detects the presence of the marker), the marker is detected and the respective ID is recognized. The algorithm is based on image segmentation which estimates the lines precisely based on the local gradient. [14,18]. Every specific marker is associated with its respective location. This localization technique has better accuracy than the 2D bar coding systems and other prevailing techniques discussed in the introduction section of the paper. It is also more robust and feasible.

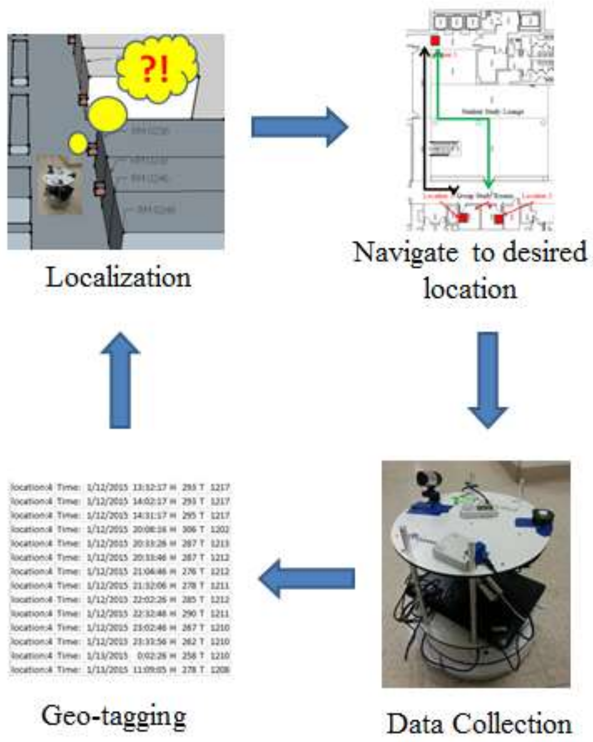

Figure 3: Sequential steps for robotic data collection in buildings

Figure 4: Fiducial markers used for localization at each location.

5.2 Navigation to desired location

The robot is tele-operated to move from the current location to the targeted location with the help of a remote laptop. First, all the required software such as ROS, ROS developer kit, TurtleBot software, and network connectivity are installed and established on the TurtleBot netbook and remote laptop. Thereafter the netbook is connected and placed on the iCreate base. Then, the remote laptop is connected to the TurtleBot's netbook with the help of Secure Socket Shell (SSH) connection in the terminal. After establishing two-way connectivity between the netbook and remote laptop, keyboard teleoperation nodes is brought up in the remote laptop. Now, with the help of key presses in the terminal, the robot can be controlled. The shortest path between the data collection locations was determined (as shown in Figure 2) and the data collection was done as described in the following section.

5.3 Data Collection

The data is collected in different locations as shown in Figure 2 with one location in the student study lounge and in two group study rooms. The readings were taken every 30 minutes as the BAS samples the pre-installed sensors at the same rate. CM-0199 COZIR® sensor along with the development kit was used for the thermal comfort data collection. The accuracy of the sensor reading is +/- 1°C of the true value and the operating conditions of the sensor range from -25°C to 55°C (-13°F to 131°F). The sensor was calibrated every time before the start of the experiment. Zero point fresh air calibration was performed which means that the sensor was placed in fresh air environment for considerable amount of time, for the temperature to stabilize and for the fresh air to completely imbue into the sensor. Echo of a particular command is noted with the new zero point reading of the sensor. Data was collected at different hours of the day with varied occupancy levels from 12/19/2014 to 12/22/2014, and from 1/5/2015 to 1/17/2015 (for a total of 17 days). The time of the day when the data was collected is enumerated in Table 2.

Table 2: Table showing the dates and times during which the data was collected

Date	From	To	Date	From	To
12/19/14	14:30	21:30	**1/10/15**	13:30	22:00
12/20/14	15:30	21:00	**1/11/15**	13:00	18:00
12/21/14	16:00	22:00	**1/12/15**	12:30	14:30
12/22/14	13:30	19:30	**1/12/15**	20:00	23:59
1/5/15	11:00	17:00	**1/13/15**	11:00	12:30
1/6/15	10:30	18:00	**1/13/15**	17:00	23:59
1/7/15	21:30	23:59	**1/14/15**	21:00	23:59
1/8/15	10:30	12:30	**1/15/15**	10:00	18:30
1/8/15	20:30	23:00	**1/16/15**	14:30	17:00
1/9/15	15:00	17:00	**1/17/15**	20:00	22:30

5.4 Geo-tagging

A python program subscribes the published ROS data regarding the location of the robot (given by the fiducial marker), concatenates it with the retrieved sensor data along with the time stamp, and exports the data to an excel file locally stored in the on-board netbook as shown in Figure 5. From left to right, information regarding the location id, date, time, humidity, and temperature values were recorded as shown.

location:1	Time:	1/13/2015	17:28:56	H	278	T	1217
location:1	Time:	1/13/2015	17:58:26	H	269	T	1216
location:1	Time:	1/13/2015	18:27:36	H	269	T	1213
location:1	Time:	1/13/2015	18:59:06	H	265	T	1213
location:1	Time:	1/13/2015	19:29:16	H	261	T	1212
location:1	Time:	1/13/2015	20:01:16	H	250	T	1212
location:1	Time:	1/13/2015	20:27:46	H	249	T	1213
location:1	Time:	1/13/2015	20:58:36	H	240	T	1210
location:1	Time:	1/13/2015	21:28:06	H	253	T	1210
location:1	Time:	1/13/2015	22:03:16	H	269	T	1210
location:1	Time:	1/13/2015	22:28:06	H	279	T	1211
location:1	Time:	1/13/2015	22:59:56	H	239	T	1209
location:1	Time:	1/13/2015	23:28:56	H	216	T	1210
location:1	Time:	1/13/2015	23:58:06	H	232	T	1210
location:1	Time:	1/14/2015	20:59:49	H	272	T	1215
location:1	Time:	1/14/2015	21:28:59	H	252	T	1211
location:1	Time:	1/14/2015	21:58:39	H	268	T	1211
location:1	Time:	1/14/2015	21:58:49	H	269	T	1211
location:1	Time:	1/14/2015	22:28:29	H	273	T	1211

Figure 5: A screenshot showing how the data is stored in an excel file in the local netbook.

6 Validation

The data collected with the help of the proposed methodology was verified with data collected by existing data collection techniques. The BAS was programmed to collect data every 30 minutes in all the locations around the clock. For example, the BAS collects and time stamps data samples at 10:30:00 AM, 11:00:00 AM, 11:30:00 AM, and so on. Since the data collected with the proposed methodology was done with a mobile robot, it is not possible to sample data in all the locations in a time synchronized way. However, the data was collected at all the locations within a stipulated time range so that it could be compared to the BAS data. Also, it is assumed that there were no significant differences in temperature values within that time frame.

There are many statistical methods to assess two types of data sets. However, given the context of comparing two data sets, t-statistic hypothesis testing was done to compare the data collected by the BAS and the robotic data mule. The absolute difference between every pair of the readings was calculated and hypothesis testing was performed for the resulting data set. Prior to the data collection using robotic data mule, experiments were also conducted in the same setting to find the difference in recorded temperature values from both the sensors (the sensor used on the robotic data mule and the thermostat in the BAS). The maximum absolute difference in the value observed was 0.88. Hence, for the statistical analysis, the null and alternate hypothesis was considered to be $|\mu_{BAS} - \mu_{Data\ Mule}| = 0.88$ and $|\mu_{BAS} - \mu_{Data\ Mule}| < 0.88$ respectively. The sample size of data at each location is 203 and hence the degrees of freedom are considered to be 202. The analysis and results are listed in Table 3.

Table 3: The hypothesis t-test analysis done for comparing the data sets collected using BAS (1) and Robotic data mule (2).

Location	$\lvert\mu_1 - \mu_2\rvert$	$\lvert\sigma_1 - \sigma_2\rvert$	t statistic	p value
1	0.4721949	0.2491279	-23.32	1.66E-59
2	0.7303503	0.8036509	-2.65	0.00043
3	1.4959223	1.0150779	8.65	1

Considering α=0.05 (confidence level of 0.95), it can be noted from the p-values in Table 3, it can be concluded that there is evidence to reject the null hypothesis and consequently the absolute difference of the values is always less than the threshold value (0.88°) for locations 1 and 2. However, there is no evidence to reject null hypothesis for location 3. Based on further investigation, we found out that the BAS sensor in the location is faulty. This is indeed one potential areas of application (finding erroneous sensors in the buildings) and advantage of collecting data with the robotic data mules. Hence, it is evident that the data collected by the robotic data mule is equivalent to the data collected by densely instrumented sensor network of BAS.

7 Conclusion

In conclusion, the new proposed methodology of indoor building energy and occupant comfort parameter data collection using mobile robots in comparison to the state of the art data collection is very effective and economical. In addition, this method does not require dense instrumentation of buildings with several fixed sensors and other systems that not only involve significant capital investment and effort, but also have perpetual issues such as maintenance, battery replacement, and sensor replacement. The sparse data collection method using a multi-sensory robotic data mule described in this paper can be easily adopted in old buildings, new buildings, and buildings with or without an existing BAS, which makes it very convenient for building managers and stake holders.

Though the robot is tele-operated to collect the data in this experiment, it does demonstrate the feasibility of the proposed idea. Similarly, the data quality of the data collected when the robot is in tele-operated mode or autonomous mode is the same. In addition, the robotic data collection platform can also be programmed to actuate controls such as turning off the lights when the space is unoccupied, or alert the building manager if air-conditioning or space heating is turned on in an unoccupied zone, and provide information regarding the real-time occupancy levels to the building manager to better control the respective areas in the building. Furthermore, this technique can be improvised to provide crucial information regarding thermal leaks, faulty building systems, and erroneous sensors to the building manager.

8 Future work

As part of future work, we are expanding the test-bed and the mobile robot to monitor and compare additional parameters such as humidity, light, occupancy, and plug load. In addition, ongoing work is focused on automating the process via a fully autonomous robot that will collect data in real-time, input the data collected in this manner into an energy simulation model of the building, and arrive at corrective actions and/or policy decisions for improving the overall energy efficiency and energy performance of the building.

9 Acknowledgments

We acknowledge the financial support received from the US National Science Foundation (NSF) CBET grant #1407908 and NSF CMMI grant #1 1414855. Any opinions in this paper are those of the authors and do not represent those of NSF.

References

[1] US Energy Information Administration (EIA) (2014). “Annual Energy Outlook 2014 Early Release Overview.” May, 2014.

[2] UNEP- United Nations Environment Programme (2007). “Buildings Can Play Key Role in Combating Climate Change.” *Sustainable buildings and climate change*, 2007.

[3] Xia, J., Hong, T., Shen, Q., Feng, W., Yang, L., Im, P., Lu, A., and Bhandari, M. “Comparison of building energy use data between the United States and China.” *Energy and Buildings* (2014).

[4] Barnes J., Rizos C., Wang J., Small D., Voigt G., and Gambale N. (2003) “Locata: The positioning technology of the future?”, presented at *6th Int. Symp. Satellite Navig. Technol. Incl. Mobile Positioning Location Services*, pp. 49–62, Melbourne, Australia, 2003.

[5] Akula, M., Dong, S., Kamat, V. R., Ojeda, L., Borrell, A., and Borenstein, J. (2011). “Integration of infrastructure based positioning systems and inertial navigation for ubiquitous context-aware engineering applications.” *Advanced Engineering Informatics*, 25(4), 640-655.

[6] Andoh, A. R., Su, X., and Cai, H., (2012). “A Boundary Condition-based Algorithm for Locating Construction Site Objects Using RFID and GPS.” *Proceedings of 2012 Construction Research Congress*, West Lafayette, IN.

[7] Zhou, Y., Liu, W., and Huang, P. (2007). “Laser-activated RFID-based indoor localization system for mobile robots.” *In Robotics and Automation, 2007 IEEE International Conference on* (pp. 4600-4605). IEEE.

[8] Liu, H., Darabi, H., Banerjee, P., and Liu, J. (2007). “Survey of wireless indoor positioning techniques and systems.” *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(6), 1067-1080.

[9] Aziz, Z., Anumba, C. J., Ruikar, D., Carrillo, P. M., and Bouchlaghem, D. N. (2005). “Context aware information delivery for on-site construction operations.” *In Proceedings of the 22nd CIB-W78 Conference on Information Technology in Construction, Institute for Construction Informatics*, Technische Universitat Dresden, Germany, CBI Publication (Vol. 304, pp. 321-332).

[10] Teizer, J., Venugopal, M. and Walia, A., (2008).

"Ultra wideband for automated real-time three-dimensional location sensing for workforce, equipment, and material positioning and tracking." *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2081, pp. 56-64.

[11] Otsason, V., Varshavsky, A., LaMarca, A., and De Lara, E. (2005). "Accurate GSM indoor localization." *In UbiComp 2005: Ubiquitous Computing, Springer Berlin Heidelberg*, pp. 141-158).

[12] Raghavan, A. N., Ananthapadmanaban, H., Sivamurugan, M. S., and Ravindran, B. (2010). "Accurate mobile robot localization in indoor environments using bluetooth." *In Robotics and Automation (ICRA), 2010 IEEE International Conference* on , pp. 4391-4396.

[13] Thrun, S., (2008). "Simultaneous localization and mapping." *Robotics and cognitive approaches to spatial mapping*, pp. 13-41.

[14] Olson, E., (2011). "AprilTag: A robust and flexible visual fiducial system." *Proceedings of IEEE International Conference on Robotics and Automation*, pp. 3400-3407.

[15] Segura, M. J., Auat Cheein, F. A., Toibero, J. M., Mut, V., and Carelli, R. (2011). "Ultra Wide-Band Localization and SLAM: A Comparative Study for Mobile Robot Navigation." *Sensors*, 11(2), 2035-2055.

[16] Ahn, H. S., and Yu, W. (2009). "Environmental-adaptive RSSI-based indoor localization." *Automation Science and Engineering, IEEE Transactions* on, 6(4), 626-633.

[17] Iwasaki, M., and Fujinami, K. (2012). "Recognition of Pointing and Calling for Industrial Safety Management." *In Proc. of the 2012 First ICT International Senior Project Conference and IEEE Thailand Senior Project Contest* (pp. 50-53).

[18] Feng, C., and Kamat, V. R. (2012). "Augmented reality markers as spatial indices for indoor mobile AECFM applications." *In Proceedings of 12th international conference on construction applications of virtual reality (CONVR 2012)* (pp. 235-24).

[19] Hanebeck, U. D., Fischer, C., and Schmidt, G. (1997, September). "Roman: A mobile robotic assistant for indoor service applications." *In Intelligent Robots and Systems, 1997. IROS'97. Proceedings of the 1997 IEEE/RSJ International Conference* on (Vol. 2, pp. 518-525). IEEE.

[20] Green, K. E., Walker, I. D., Gugerty, L. J., and Witte, J. C. (2006). "Three robot-rooms: the AWE project." *In CHI'06 Extended Abstracts on Human Factors in Computing Systems* (pp. 809-814). ACM.

[21] Boltr (2014), "SaviOne robot butler starts room service deliveries this week" online < http://www.savioke.com/> [Accessed: Dec'4th, 2014].

[22] Linner, T., Güttler, J., Bock, T., and Georgoulas, C., (2015). "Assistive robotic micro-rooms for independent living." *Automation in Construction*, 51 (2015) pp. 8–22.

[23] Pérez-Lombard, L., Ortiz, J., and Pout, C. (2008). "A review on buildings energy consumption information." *Energy and buildings*, 40(3), 394-398.

[24] Fisk, W. J. (2000). "Health and productivity gains from better indoor environments and their relationship with building energy efficiency." *Annual Review of Energy and the Environment*, 25(1), 537-566.

[25] Azar, E., and Menassa, C. C. (2014). "A comprehensive framework to quantify energy savings potential from improved operations of commercial building stocks." *Energy Policy*, 67, 459-47. .

[26] Azar, E., and Menassa, C. (2012). "A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings." *Energy and Buildings*, 55, 841-853.

[27] Yudelson, J. (2010). "Sustainable retail development." *Energy Efficiency Measures, Springer*, Tucson, Arizona 38-39.

[28] Bordass, B., Cohen, R., Standeven, M., and Leaman, A. (2001). "Assessing building performance in use 3: energy performance of the Probe buildings." *Building Research and Information*, 29(2), 114-128.

[29] Hu, X. (2011). "Dynamic data driven simulation." SCS M&S Magazine, 1, 16-22.

[30] Mathews, E. H., Botha, C. P., Arndt, D. C., and Malan, A. (2001). "HVAC control strategies to enhance comfort and minimise energy usage." Energy and Buildings, 33(8), 853-863.

[31] Bradshaw, V. (2010). "The building environment: Active and passive control systems." Human Comfort and Health Requirements, *John Wiley and Sons* pp 3-36.

[32] Olofsson, T., Andersson, S., and Sjögren, J. U. (2009). “Building energy parameter investigations based on multivariate analysis.” *Energy and Buildings*, 41(1), 71-80.

[33] VonNeida, B., Manicria, D., and Tweed, A. (2001). “An analysis of the energy and cost savings potential of occupancy sensors for commercial lighting systems.” *Journal of the Illuminating Engineering Society*, 30(2), 111-125.

[34] Williams, A., Atkinson, B., Garbesi, K., Page, E., and Rubinstein, F. (2012). “Lighting controls in commercial buildings.” Leukos, 8(3), 161-180.

[35] Wilkinson, S. J., Reed, R., and Jailani, J. (2011). “User satisfaction in sustainable office buildings: a preliminary study.” In PRRES 2011: Proceedings of the 17th Pacific Rim Real Estate Society Annual Conference. Pacific Rim Real Estate Society.

[36] Zagreus, L., Huizenga, C., Arens, E., and Lehrer, D. (2004). “Listening to the occupants: a Web based indoor environmental quality survey.” *Indoor Air,* 14(s8), 65-74.

[37] Abbaszadeh, S., Zagreus, L., Lehrer, D., and Huizenga, C. (2006). “Occupant satisfaction with indoor environmental quality in green buildings.” *Proceedings of Healthy Buildings 2006*, Lisbon, Vol. III, 365-370.

[38] Edwards, B. (2006). “Benefits of green offices in the UK: analysis from examples built in the 1990s.” *Sustainable Development,* 14(3), 190-204.

[39] Neto, A. H., and Fiorelli, F. A. S. (2008). “Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption.” *Energy and Buildings*, 40(12), 2169-2176.