Ambient Data Collection in Indoor Building Environments Using Mobile Robots

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Abstract –

Building designers have increasingly looked at simulation to improve the performance of building systems with the primary objective of simultaneously maximizing comfort, and minimizing energy use. The quality of the simulations depends on the quality of the data being input into the models. The input data for simulation comprises the current real state of a building which encompasses several components that include the state of occupants, comfort parameters, and the building systems. Typically, such data is aggregated using preinstalled Building Automation Systems (BAS) with the help of stationary wired or wireless sensor networks. Such a process is cost-prohibitive, time consuming, and often impractical in existing buildings without BAS. This paper proposes mobile platform based robotic data collection for gathering energy and comfort related data in real-time which can be utilized for further simulation analysis and decision-making. The fiducial marker based navigation and drift correction algorithms developed to facilitate the robotic platform navigation in a building are discussed in detail. This method successfully achieves the navigation task by providing directional navigation information along with drift correction at critical discrete locations instead of the traditional continuous updating process, which is computationally intensive. An experimental study validating the statistical equivalence of the two data sets gathered by the traditional preinstalled fixed sensor networks and the multi-sensor fused robot was performed. The results demonstrate the feasibility of the proposed methodology in efficiently collecting large datasets in buildings using only a single set of sensors in contrast to the scads of similar sensors required by traditional data collection methods.

Keywords –

On-line Simulation, Data Collection, Indoor robots, Navigation and Drift correction algorithms.

1. Introduction

Buildings are responsible for 40% of the total energy consumption in the Unites States (US) [1]. According to US EIA 2014, future predictions show that these energy demands will continue to increase indicating a significant need for innovative efforts to optimize the energy consumption of buildings. The United States Green Building Council (USGBC) suggests that commissioning and/or retrofitting is the process through which buildings can be efficiently operated to achieve high performance [2].

Effective energy retrofits or commissioning process requires a comprehensive understanding of all the building systems, energy use behavior of the occupants, energy performance of the building, and changing weather patterns [3]. It is thus apparent that a significant amount of data needs to be continuously collected, managed, and analyzed in a building at the room and floor level in order to effectively optimize energy use in buildings while maintaining comfort of the occupants. Building energy simulation plays a key role in analyzing the aforementioned building energy data [4]. Several existing studies demonstrate how the data in real-time or near real-time or in offline/batch processing mode can be used for critical decision making in buildings [5,6].

Building energy and comfort parameter data collection has progressed significantly in the past few years because of the advancements in technology. In the early stages, inspectors used to collect data manually by inspecting different locations in the building, a process considered to be extremely tedious, time consuming and generates limited amounts of data which limits its practical applicability in large buildings [7-9].

With the advent of wired and wireless sensors, significant effort was saved by avoiding the need of manual inspection during the operation and maintenance phase of the buildings. Instead, in the newer buildings, sensors are installed, calibrated, and integrated with building systems before the operation and maintenance phase as part of a Building Automation System (BAS). However, this process is not very feasible for the existing buildings because of the challenges involved in installing the wiring, integrating with existing building systems, and calibrating the sensors.

Wired systems are most commonly used for video surveillance applications in residential or commercial buildings because of higher band width and power needs [10]. These are economically feasible for smaller buildings compared to larger buildings (e.g., dormitory buildings, academic institutions, and office spaces) where there are a large number of rooms that need to be monitored. This is because installing a wired system in an existing building requires additional costs associated with material (e.g., wiring) and labor intensive task of installation [11,12]. In addition, wired installation process is time consuming and sometimes limits the extent of space that can be monitored [12-14].

On the other hand, wireless systems have a capability to monitor, process, analyze the data locally, and eliminate the need of wires [13,15]. Wireless sensor networks are widely used for monitoring and controlling various indoor parameters such as temperature, humidity, CO2 levels, occupancy level, occupancy comfort, and water use [14]. However, they are expensive (due to a lot of initial upfront investment for large buildings), complex (due to installation of lot of sensors), time consuming (due to periodic calibration and maintenance requirements), and not feasible in existing buildings due to the need to install a BAS. In addition, existing buildings undergo retrofitting or retro-commissioning to improve the energy performance, which makes it even more time consuming, tedious, and expensive to uninstall, reinstall, recalibrate, and integrate with the BAS of the building. Wireless systems also suffer from power consumption, scalability, and limited information storage capacity issues limiting the extent and quality of the data that can be collected [7,16]. Further details about these data collection methods along with a thorough analysis of the respective characteristics can be found in [17].

In an aim to mitigate the aforementioned issues, this paper introduces a mobile platform based data collection process that uses mobile indoor robot equipped with single set of sensors. The mobile robot is capable of navigating in a known indoor environment with the help of onboard sensor suite (for data collection), onboard computing capabilities, and a RGB camera (for localization, navigation, and drift correction). The entire process of robotic navigation along with the localization, data collection, and geotagging are discussed in detail in the methodology section of the paper. One of the main advantages of the proposed data collection method is that it eliminates the need for instrumenting different locations in existing buildings with the same set of sensors [18]. The case study described at the end of this paper illustrates how the robot is capable of providing a rich data set for energy retrofit and/or retro-commissioning decision making purposes.

2. Research Objectives

The main goal of this study is to introduce a new data collection technique for gathering information regarding energy and comfort related parameters in buildings. The proposed approach is more economical and feasible compared to the existing techniques. The data collected using this approach has the potential to assist building managers in making timely and informed decisions about retrofitting and/or commissioning of the buildings which does not have the latest BAS installed. Thus, the primary objectives of this paper are to 1) Introduce a novel concept of using mobile indoor robots for collecting energy and comfort related data in buildings, 2) Discuss in detail the localization, navigation, and drift correction algorithms for two of the three robotic platforms developed. 3) Statistically compare the quality of the data sets collected using the traditional BAS and the mobile robot to illustrate the applicability of this framework for energy analysis in buildings.

3. Design of the Robot

One of the main contributions of this paper is the design of the robot along with its respective algorithms which are the basis for robots' navigation. Some of the other 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 robot), 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 mobile robots required to monitor (depending on the size of the buildings) the entire building, optimizing the travel time and path.

The TurtleBot robot platform, equipped with the iCreate base is chosen as the mobile data collection platform and sensors such as Cozir® CM 0199 (for temperature, humidity, and CO2 levels), HOBO U12 (for light and occupancy levels), Lutron (for natural light levels), NinjaBlocks (for air speed), Smart meters (for electricity consumption) is 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 detect fiducial markers, localize, and estimate its relative pose in an indoor environment; 4) Remote laptop for executing the corresponding navigation programs on the on-board netbook; and 5) Sensors – for monitoring and data collection of various occupant comfort and building energy parameters.

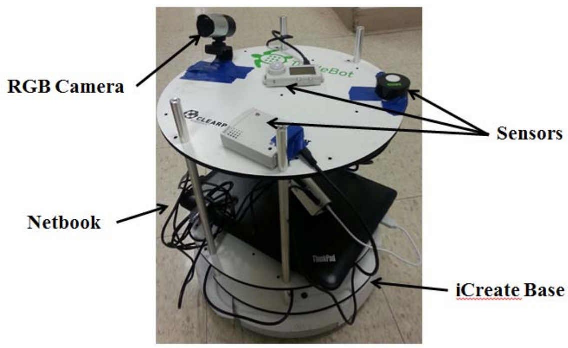

Figure 1. Components of the robot used for occupant comfort and indoor environmental data collection

4. Methodology

In order for the robot to autonomously navigate indoors and collect energy and comfort related data, it needs to 1) localize in the indoor environment, 2) navigate to the intended data collection locations, 3) collect the respective data (such as temperature, humidity, and light intensity), and 4) geo-tag (record the collected data with the physical location) for further analysis.

In the current context, localization of a robot means that the robot needs to be able to identify its current location in a known indoor environment setting. For example, a robot being able to recognize its current location to be in room 201, or knowing its xy location and orientation in the global coordinate reference system. The robot's navigation can be briefly defined as the robot's ability to plan a course of action to reach the destination location while accurately localizing itself in its frame of reference at strategic locations [19].

Many non-visual sensor based (non-vision based) techniques such as Global Positioning System (GPS) [20], Radio Frequency Identification (RFID) [21,22], Wireless Local Area Network (WLAN) [21,23], Ultra-Wide Band (UWB) [24], Bluetooth [25], and Inertial Measurement Unit (IMU) [26] used to be the primary focus of many studies for localization and navigation indoors. Though GPS and UWB have good accuracy, they require Line Of Sight (LOS) and tend to be costly. RFID is comparatively cost effective but for good accuracy a large number of tags are required. WLAN and IMU suffer from dynamic environment changes and drift accumulation respectively. Bluetooth based technologies require dense instrumentation of the beacons in the environment.

With the advent of efficient computing capabilities and developments in the field of computer vision, techniques such as Simultaneous Localization and Mapping (SLAM) [27] and visual registration which utilize visual sensors such as cameras, laser scanners [28,29] or LIght Detection And Ranging (LIDAR) were developed. Though 3D pose estimation is possible in most of the vision based techniques, they suffer some of the disadvantages such as requirement of high computational power, infrastructure dependency, and higher costs.

One of the vision-based methods reviewed (Fiducial Markers), however, is particularly immune to the aforementioned disadvantages afflicting other methods. Fiducial markers [30] offer high accuracy in determining and estimating their relative 3D pose in an environment, require relatively less computing capabilities, are cost-effective, and are easy to install [31].

4.1 Localization

In this section, the general computing framework that is developed as part of this research is described. This framework uses fiducial markers to link between actual physical locations and virtual information stored regarding those locations) for indoor robot localization.

Fiducial markers have the capability to store virtual information regarding multitude of things such as information regarding physical location (floor and room level information), emergency evacuation directions, indoor navigational information, and inspection related data regarding building systems helpful for facility managers [32]. For this study, unique fiducial markers are required to be placed along the navigational path of the robot (e.g., corridors, entrances to rooms etc.) as shown in Figure 4. More information on characteristics and properties of the markers is available in [30]. These markers, which are printed on regular paper, are used to store the physical location information (e.g., Room 101) and navigational information (e.g., take right) which is necessary to help the robot determine its current location and its targeted headed direction.

4.2 Navigation

Three different kinds of navigation techniques namely tele-operated, predefined path mode, and dynamically configurable path mode were developed by the authors. The former is discussed in [18] and the latter two are discussed in detail in this study. The complexity of the algorithm increases and human involvement decreases respectively. Tele-operated navigation (where human operator drives the robot remotely using a laptop or a wireless controller) is most suited for places which are highly reconfigurable and need sporadic data collection such as banquet halls, training rooms, and convention facilities. Predefined path mode navigation is mostly suited for places with regular occupancy and almost fixed spaces which require periodic data collection (Every 15 minutes or 30 minutes) such as offices, data centers, and ware houses. Dynamically configurable path mode is highly applicable for flexible/ dynamically changing occupancy buildings where data collection locations change dynamically depending on occupancy all through the day such as retail stores, schools, colleges, shopping malls, and airports. The navigation logic for each of these two types is described in detail in the following paragraphs. In addition, they are semi-autonomous because obstacle avoidance is not considered in the navigation.

4.2.1 Predefined path mode

In this mode, the robot is given a predefined path with a start location, end location, the path it needs to autonomously traverse to reach the end location, and also the data collection locations along the way. Several markers whose global positions and orientations are known in advance are placed at regular intervals along the navigational path as shown in Figure 4.

The overview of the navigational algorithm logic is represented as a flowchart in Figure 2. First, the aboard traditional RGB camera continuously captures images that might potentially contain a known fiducial marker. The images are processed by the marker recognition module (an algorithm which detects the presence of the marker). If a known marker is detected by the marker recognition module, the ID and relative pose of the robot with respect to the fiducial marker (in the camera's reference frame) is outputted by the module. Each ID is associated with a physical location in the indoor environment as shown in Figure 4. Current location of the robot based on the aforementioned information is estimated and pose correction is calculated based on the drift correction algorithms discussed later in this section of the paper. The current approach of navigation can be termed as treasure hunt based navigation because the robot traverses the path from one marker to another marker with the help of clues provided at each marker. This means that robot will follow the previously known navigational direction (or clue provided by the last seen marker) until it finds a new marker. To avoid the cases of obstruction (robot not being able to see one or two markers in the navigation path), it can be easily programmed to store information regarding next couple of markers and still traverse the navigational path accordingly.

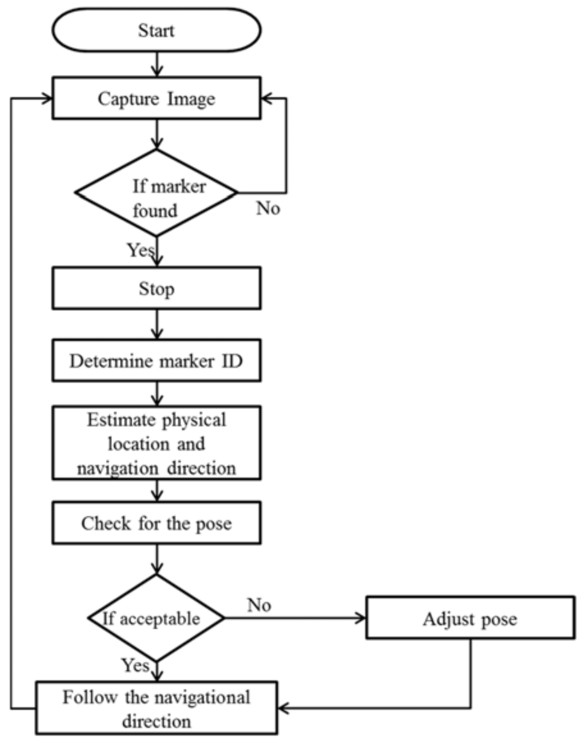

Figure 2. Indoor treasure hunt based navigation algorithm with the help of network of fiducial markers

Drift Correction (Predefined path): Drift is one of the major areas of concerns in the field of autonomous robots [33]. One of the most important factors that have a direct impact on whether the robot will traverse the entire path is drift accumulation of the robot. In this study, negative drift (-ve drift) means that the robot has drifted inwards (towards the marker) and conversely positive drift (+ve drift) means that the robot has drifted outwards (away from the marker).

The current drift correction algorithm developed is based on the relative pose information estimated with the help of the onboard camera, computer, the known marker's pose, and the known location in the fiducial markers network. The algorithm returns 3D relative pose information (as shown in Eq. 1) in camera reference frame with respect to the marker. From that, the lateral distance information (distance between the camera and marker), d as shown in Figure 3, is extracted and the drift at each location (δdi) is estimated. After that, the pose correction (turning angle (αi) in this case) is calculated based on the equations developed as shown in Eq. 2 and 3 along with a detailed description of various parameters are shown in Figure 3. Since the drift at each location might be different, the turning angle at each location also differs.

$$\boldsymbol{H} = \begin{matrix} \boldsymbol{R11} & \boldsymbol{R12} & \boldsymbol{R13} & \boldsymbol{Tx} \\ \boldsymbol{R21} & \boldsymbol{R22} & \boldsymbol{R23} & \boldsymbol{Ty} \\ \boldsymbol{R31} & \boldsymbol{R32} & \boldsymbol{R33} & \boldsymbol{Tz} \end{matrix} \dots\dots\dots\dots\dots\dots\dots . \boldsymbol{Eq(1)}$$

Where:

H is the part of Homogeneous transform matrix returned by the localization algorithm

R: Rotation matrix

T: Translation matrix

$$\boldsymbol{\alpha 1 = 2 * \tan^{-1}\left(\frac{\delta d}{M}\right)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . \boldsymbol{Eq(2)}$$

$$\boldsymbol{\alpha i = 180 - \tan^{-1}\left(\frac{\frac{M}{\delta di}}{1 + \left(\frac{\delta d(i-1)}{\delta di}\right)}\right) - \tan^{-1}\left(\frac{M}{\delta di}\right) \forall\, i \geq 2} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. \boldsymbol{Eq(3)}$$

4.2.2 Dynamically configurable path mode

In this mode, navigation is based on user inputted coordinates which also allows the user to configure the robot's path dynamically. This mostly resembles and matches the criteria for real-world applications where the robot might have to traverse different paths during different times of day.

The overarching logic of the entire algorithm is the same as previously discussed and shown in Figure 2. However, the drift correction technique differs in this algorithm when compared to the previously discussed (Predefined path mode) algorithm. The navigational direction is estimated with the help of user inputted coordinates by generating vectors based on adjacent pair of coordinates and calculating the angle between the pair of vectors

Drift Correction (dynamically configurable path): Similar to the drift correction algorithm discussed in the previous section, the current drift correction algorithm also works based on the relative pose information estimated with the help of the onboard camera, computer, the known marker's pose, and the known location in the fiducial markers network. However, instead of calculating the lateral distance between the camera and the fiducial marker detected, this system estimates the relative pose angle between the plane of the marker and the plane of camera in cameras reference frame. The angle determined is termed as adjusted angle and it is added to the calculated angle in the navigation logic discussed above. Thus, a net corrected angle (based on the calculated angle and adjusted angle) is calculated and the robot instead of turning the entire calculated angle, rotates only the amount of corrected angle thereby, correcting its drift. The same process is continued at every marker location until the destination/ targeted location is reached.

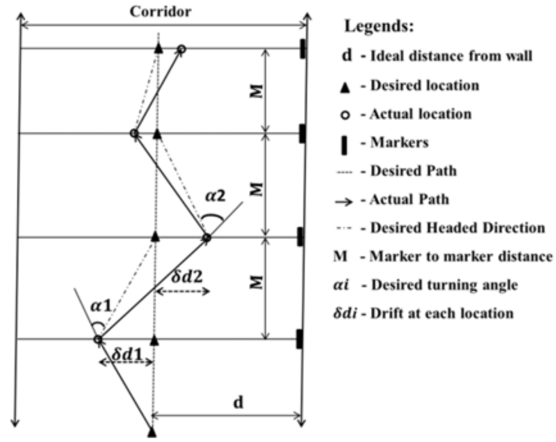

Figure 3. Visual representation of the drift error and respective terminology used in the drift correction algorithms.

4.3 Data Collection and Geo Tagging

The immediate next step once the robot is cognizant of its surroundings and capable of navigating indoors is collecting data. In the context of this paper, the parameters of interest are occupants comfort data in buildings such as temperature, humidity, indoor air quality, and light intensity.

In this study, geotagging is associating the building energy/ thermal comfort data collected along with its location information such as room number and floor number. To achieve this, a programmable interface is developed which bridges the communicated physical location information (as given by the fiducial markers) with the sensor data (obtained from the data collection). A python program is written which 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. This data then can be stored in a local server or can be updated to an online big data set interface for further real-time processing/ analysis.

5. Case Study

A case study was performed to show the validity of all the four steps of methodology. Experiments were conducted in the Ross School of Business at the University of Michigan - Ann Arbor campus with the help of turtlebot as a mobile platform (as discussed in section 3 of this paper). 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, and damper status operation. The basement floor comprising of an open study lounge (monitored by four thermostats) and the open corridor (monitored by three thermostats) were chosen as the test bed for the case study experiments. Figure 4 shows the locations of the thermostats and/or the locations in the basement where the temperature readings are recorded by the BAS. Since the case study location chosen consists of public spaces (corridors and open student lounge) with dynamically changing occupancy levels, dynamically configurable path mode technique as discussed in the navigation section of the methodology is chosen for the robot data collection path. However, the type of navigation technique used will not have any effect on the quality of the data collected.

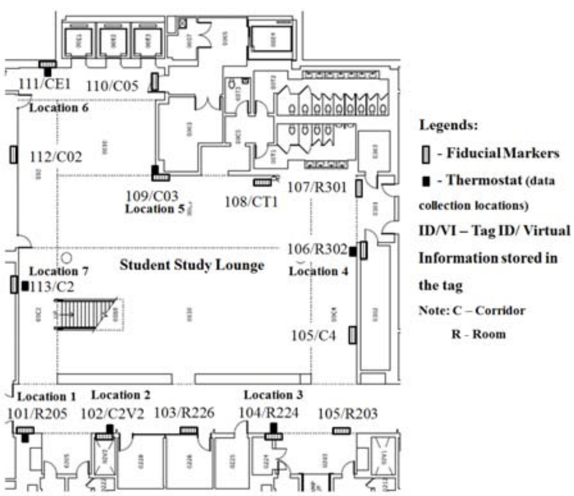

Figure 4. Fiducial marker network with the virtual information regarding the location stored in each of the markers along with the data collection locations in the basement floor of Ross School of Business, University of Michigan – Ann Arbor.

5.1 Validation

The data collected with the help of the proposed methodology is verified with data collected by existing technique using BAS. The BAS is 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 is done with a mobile robot, it is not possible to sample data in all the locations in a time synchronized way. However, the data is collected at all the locations within a stipulated time range so that it can 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 robot. 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, 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 robot and the thermostat in the BAS). The maximum absolute difference in the value observed was 0.8. Hence, for the statistical analysis, the null and alternate hypothesis were considered to be $|\mu_{BAS} - \mu_{Robot}| \leq 0.8$ and $|\mu_{BAS} - \mu_{Robot}| > 0.8$ respectively. The sample size of data at each location is 202 and hence the degrees of freedom are considered to be 201. The analysis and results are listed in Table 1.

Table 1 Results of paired test analysis done for comparing the data sets collected using BAS (1) and Mobile robot (2).

Location	$\|\mu 1 - \mu 2\|$	$\|\sigma 1 - \sigma 2\|$	t statistic	p value
1	0.283	0.184	-39.90	1
2	0.491	0.347	-12.67	1
3	0.466	0.262	-18.09	1
4	0.446	0.366	-13.76	1
5	0.647	0.491	-4.44	0.99
6	0.603	0.389	-7.20	1
7	0.493	0.453	-9.63	1

Considering α=0.05 (confidence level of 0.95), it can be noted from the p-values in Table 1that there is no evidence to reject the null hypothesis. Hence, it is evident that the data collected by the mobile data collecting platform is equivalent to the data collected by densely instrumented sensor network of BAS.

6. Conclusion

The proposed methodology of mobile indoor robotic monitoring and data collection of indoor environmental and occupant comfort parameters discussed in this paper offers an effective and economical method as compared to the traditional state of the art (Fixed stationary sensor network) data collection methods. This method involves using mobile indoor robots equipped with sensors to monitor and collect energy and comfort related data in buildings. It is particularly significant for old buildings that do not have an installed sensor network. With meager instrumentation of markers in buildings, the required data can be collected with the help of mobile robots.

Some of the main characteristics of the traditional (stationary/fixed) sensor networks and mobile robotic data collection are descried as follows. A) Upfront Costs: Fixed sensor networks need astronomical amount of sensors, while mobile based systems need only one set of sensors. B) Initial setup: Need to install and calibrate thousands of sensors in each room in a building. Though mobile based system requires installing markers in the environment, they are easily configurable and the calibration needs to be done only on one set of sensors. C) Operational and Maintenance Costs: For fixed systems, high manual and administrative costs are incurred for periodic battery replacement, maintenance, and calibration for each of these sensors. Locating these sensors may prove to be a challenge in complex buildings. On the other hand, it is comparatively a lot easier to perform the aforementioned tasks on one set of sensors. With regard to the runtime power consumption of the robot, it is envisioned that the robot will autonomously charge itself (similar to existing robotic platforms such as Roomba) when the battery is running low and resume the data collection. D) Frequency of data collection: Fixed systems are capable collecting data with any time interval, but mobile platforms are limited based on the area that needs to be monitored.

In addition, the limitations of the proposed system include requirement of marker instrumentation in the environment and occlusions. Careful consideration is required for determining the placement of the markers, as they might suffer from occlusions. However, with minor alterations in the algorithm, it can be programmed to account for the occluded markers. These markers are very easy to deploy and configure [32].

Future planned work includes addition of obstacle avoidance methods to the existing algorithms and subsequently testing the robot in more complex indoor environments.

7. Acknowledgments

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