Multi-dimensional Mapping of Confined Areas using a Hexapod Robot with Integrated Sensor Data and SLAM

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Abstract –

Mobile robots are increasingly used to explore and inspect confined environments, often in situations that are hazardous or inaccessible to humans, highlighting the need for advanced mapping and sensing capabilities. This paper presents a novel approach for constructing a multi-dimensional map by integrating sensor data from a hexapod robot with Simultaneous Localization and Mapping (SLAM). The robot, equipped with a DHT22 sensor and powered by a Raspberry Pi 4 Model B, was deployed in a mechanical room at the University of Alberta to collect humidity and temperature data while simultaneously mapping the environment. The Cartographer SLAM algorithm was used for mapping, and the sensor data was fused with the generated map by the Inertial Measurement Unit (IMU) using a bilinear interpolation algorithm. This pilot experiment serves as a demonstration of the proposed robot system, which results in a multi-dimensional map that combines 2D geographical map with sensory maps such as humidity and temperature. The map provides a visualization of the spatial distribution of environmental variables within the confined area. This approach has potential applications in various scenarios, including quick mapping of hazardous areas and routine inspections of areas with limited access. Future work will focus on incorporating 3D SLAM and exploring the use of machine learning techniques for automated anomaly detection within the multi-dimensional map, while addressing the current limitations related to real-time processing and visualization.

Keywords –

Mobile Robotics, Simultaneous Localization and Mapping (SLAM), Sensor, Inspection

1 Introduction

Mobile robots play an increasingly important role in exploring and inspecting unstructured and confined environments, particularly those deemed hazardous or inaccessible to humans [1]. A key capability for such robots is the ability to generate accurate maps of the environment while simultaneously localizing themselves within that map, even the environment is deviated from its original plan [2]. This is commonly achieved through Simultaneous Localization and Mapping (SLAM) techniques [3]. It leverages sensor data from LiDAR and cameras to enable robots to autonomously explore unknown environments and create detailed maps for navigation and task execution [3].

However, conventional SLAM algorithms predominantly focus on geometric mapping, primarily capturing the spatial layout and structural features of the environment [4]. While crucial for navigation and obstacle avoidance, these geometric maps often lack information about other critical environmental variables that can significantly impact a robot's operation or the understanding of the surrounding space [5]. Monitoring factors such as temperature, humidity, air quality, and the presence of hazardous substances is essential for robots deployed in applications such as environmental monitoring [6], industrial inspection [7], and disaster response [8]. Moreover, the map integrated with multi-dimensional layers can also enhance the situational awareness of decision makers [9]. In summary, a crucial research gap exists in multi-dimensional mapping with SLAM: the existing techniques primarily focus on geometric mapping, neglecting the integration of environmental variables crucial for understanding and operating in complex confined areas.

Researchers have explored several detection and mapping methodologies for construction environments. Borrmann, et al. [10] introduced a system utilizing a mobile robot equipped with 3D laser scanners, RGB cameras, and thermal cameras to generate 3D thermal maps of buildings, designed to identify heat leaks and infrastructure anomalies. Amigoni and Caglioti [11] focused on efficient exploration by developing an information-based strategy for mobile robot mapping, employing laser range scanners and balancing travel distance with information gain. Although these studies effectively demonstrate the utility of mobile robots for inspection and mapping in confined spaces, they often prioritize either geometric reconstruction or specialized sensor-based detection, leading to a lack of integrated, multi-sensory map outputs. This research seeks to bridge this gap by integrating geometric and sensory mapping techniques, advancing mobile robot functionality beyond standard SLAM and detection to encompass comprehensive SLAM and sensory mapping, providing a richer environmental representation.

To fill the gap, this research investigates a method to integrate sensor data with SLAM to create a multi-dimensional map that provides a richer and more comprehensive understanding of the environment. By fusing data from environmental sensors with the spatial information obtained through SLAM, a more holistic representation of the confined area can be achieved. This multi-dimensional map not only captures the geometric features but also incorporates crucial environmental variables, enabling a more informed analysis of the surrounding space.

This research investigates the use of a hexapod robot equipped with a DHT22 sensor to create a multi-dimensional map of temperature and humidity within the mechanical room of the Li Ka Shing building at the University of Alberta. This mechanical room serves multiple key virology laboratories and requires a high level of environmental monitoring. In this pilot experiment, the goal was to investigate the robot system's capabilities to constructing a multi-dimensional map. By integrating Inertial Measurement Unit (IMU) information, the sensor data was then fused with the 2D map generated by the SLAM algorithm to create a multi-dimensional map with sensor data, enabling the visualization of the spatial distribution of temperature and humidity within the confined space.

This paper details the methods used for sensor integration, data acquisition, and map generation, and discusses the challenges encountered and potential applications of this approach. The findings contribute to the development of more comprehensive mapping techniques for robots operating in complex and confined environments, ultimately enhancing their capabilities in various real-world scenarios. The paper contributes to overcome the barriers of adopting sensors in construction industry, specifically in Multi-sensor Data Fusion and Decision Support Integration [12].

2 Robotic System Design

The high-level robotic system design employed in this research, illustrated in Figure 1, adopts a client-server architecture to facilitate both manual and semi-autonomous operation. This architecture allows for a modular and scalable approach, where the robot platform itself functions as the server, managing onboard processes such as data acquisition from the LiDAR and DHT22 sensors, as well as executing the Cartographer SLAM algorithm. The server also handles the alignment of sensor data with the SLAM-generated map using the IMU. The client-side, typically a separate computer, focuses on real-time visualization of the robot's progress and the construction of the final multi-dimensional map. This division of tasks between server and client enhances the efficiency of the system, particularly given the computational constraints of the Raspberry Pi used on the robot platform. Communication between the server and client is established wirelessly via TCP/IP over Wi-Fi, enabling remote control and monitoring of the robot's operations.

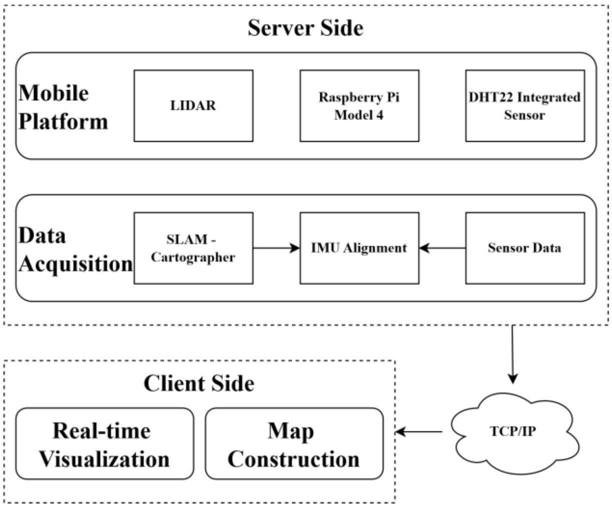

Figure 1 High-level Robotic System Design

2.1 Robot Platform

The robot prototype used in this research is a custom-assembled hexapod robot based on a Raspberry Pi 4 Model B. The Raspberry Pi serves as the central processing unit, responsible for controlling the robot's locomotion, sensor data acquisition, and communication. The robot's design is based on the RHex [13]. The choice of a hexapod robot for this research was motivated by several factors related to the challenges of navigating and collecting data within confined areas [3]. Hexapod robots offer superior mobility compared to wheeled or tracked robots, enabling them to traverse uneven terrain, overcome obstacles, and maintain stability in confined spaces. Their adaptability to different locomotion gaits allows them to maneuver effectively in tight spaces and adjust to varying environmental conditions [14]. Additionally, the hexapod platform's inherent stability ensures that the robot can maintain its balance while carrying the necessary sensors and computing equipment, crucial for acquiring reliable data in potentially unstable environments [15]. The combination of mobility, adaptability, and stability makes the hexapod robot an ideal choice for this research.

2.2 Sensor Integration

The robot prototype was equipped with a DHT22 sensor to measure temperature and humidity. This sensor was chosen for its affordability, ease of use, and compatibility with the Raspberry Pi [16]. The DHT22 sensor was connected to the Raspberry Pi's GPIO (General Purpose Input/Output) pins, and the sensor data was read using the Adafruit_DHT library. This library provides functions for interacting with the DHT22 sensor and retrieving temperature and humidity readings [17]. Incorporating sensors with single sensing principle, such as temperature and humidity sensors, in this initial prototype is beneficial as it provides a foundational framework for integrating environmental data with SLAM, enabling the robot to assess basic environmental conditions and serving as a stepping stone towards more complex sensing capabilities for applications such as detecting thermal anomalies in industrial settings or identifying potential gas leaks [1].

2.3 SLAM Implementation

The Cartographer SLAM algorithm was employed for mapping the environment, which is visualized in real-time using Rviz, as shown in Figure 2. Cartographer is an open-source SLAM library developed by Google, known for its accuracy and robustness in various environments. It utilizes a combination of laser range finder data and inertial sensor data to create a 2D map of the surroundings [18]. In this research, the robot's movement was controlled manually, and the Cartographer SLAM algorithm generated a map of the confined area based on the robot's trajectory and sensor readings.

In order to provide the Cartographer SLAM algorithm with the necessary spatial information, a LiDAR (Light Detection and Ranging) sensor was integrated into the robot's platform. The LiDAR sensor emits laser beams and measures the time it takes for the beams to reflect back from surrounding objects, providing accurate distance measurements [19]. This data was then used by the Cartographer SLAM algorithm to construct a detailed map of the environment, including walls, obstacles, and other features. The integration of the LiDAR sensor enhances the accuracy and efficiency of the mapping process, enabling the robot to generate a comprehensive representation of the confined area [19].

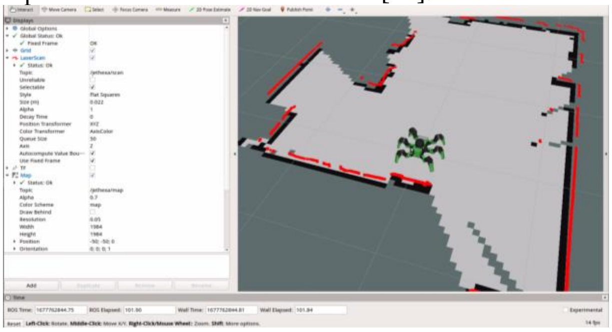

Figure 2 RViz Visualization of SLAM

2.4 Control and Communication

The robot's control and communication systems were designed to facilitate both manual and semi-autonomous operations. A client-server architecture was implemented, allowing for remote control and monitoring of the robot's activities. The server-side program, running on the Raspberry Pi, managed sensor data acquisition, SLAM processing, and communication with the client. The client-side program, running on a separate computer, provided a graphical user interface (GUI) for controlling the robot's movements, visualizing sensor data, and monitoring the mapping process.

Communication between the client and server was established over a Wi-Fi network using the TCP/IP protocol. This wireless communication enabled real-time control of the robot and allowed the operator to monitor the robot's progress and sensor readings from a safe distance. The client-server architecture provided flexibility in controlling the robot and facilitated the integration of additional sensors or functionalities in the future.

2.5 Data Acquisition

The robot prototype was deployed in a section of mechanical room of the Li Ka Shing building at the University of Alberta, as shown in Figure 3. The mechanical room served as a representative confined area, characterized by limited space, obstacles, and varying environmental conditions. In this pilot experiment, the goal was to investigate the robot system’s capabilities for constructing the multi-dimensional map. The robot was manually controlled to traverse the room, and the DHT22 sensor collected temperature and humidity data at one-second intervals. This sampling rate was chosen based on the sensors response frequency (0.5 Hz or once every two seconds) and the robot’s stabilization time (one second). The readings will be normalized to ensure the accuracy of values in Section 2.6. The Cartographer SLAM algorithm generated a 2D map of the room based on the robot's movement, and the IMU integrated with sensor readings generated another two 2D maps for temperature and humidity.

Figure 3 Mechanical Room for the Experiment

To enhance the visualization and analysis of the acquired sensor data, a real-time bilinear interpolation algorithm was employed [20]. This technique estimates values at intermediate points within the 2D map based on the known sensor readings at surrounding locations [21]. By interpolating the temperature and humidity data, a continuous heatmap representation can be generated, providing a more comprehensive view of the environmental conditions within the confined area. Bilinear interpolation is computationally efficient and offers a reasonable approximation of the spatial distribution of sensor data, making it suitable for this application [20].

The bilinear interpolation is calculated as follows:

Let Q_{11}, Q_{12}, Q_{21}, and Q_{21} represent the temperature or humidity values at the four points of a grid cell and let $P_{(x,y)}$ be the point where the interpolated value is needed.

Interpolate in the x-direction:

$$R1 = \frac{(x_2 - x)}{(x_2 - x_1)} * Q_{11} + \frac{(x - x_1)}{(x_2 - x_1)} * Q_{21}$$

$$R2 = \frac{(x_2 - x)}{(x_2 - x_1)} * Q_{12} + \frac{(x - x_1)}{(x_2 - x_1)} * Q_{22}$$

Interpolate in the y-direction:

$$p = \frac{(y_2 - y)}{(y_2 - y_1)} * R_1 + \frac{(y - y_1)}{(y_2 - y_1)} * R_2$$

In these equations, Q represents the value of the environmental variable being interpolated using single sensing principles, whether it is temperature, humidity, or any other measured quantity. For points Q11, Q12, and Q22 that lie on the robot's trajectory, their temperature and humidity values can be directly measured by the onboard sensors. However, for the point Q21 located outside the trajectory, the value was estimated by interpolation based on the known values of its three closest neighbours (Q11, Q12, Q22) in the corresponding points in the adjacent grid cell. This approach leverages the spatial correlation between neighbouring points to provide a reasonable approximation of the environmental conditions at Q21. This generalized notation emphasizes the versatility of bilinear interpolation, as the same mathematical framework can be applied to various environmental parameters.

It is important to acknowledge that assuming a linear distribution for temperature and humidity may not always be accurate, especially in environments with complex variations. More sophisticated interpolation techniques, such as kriging [22] or Gaussian process regression [23], could be explored to better capture the spatial distribution of these variables. These methods can account for spatial correlations and provide more accurate predictions, but they also require more computational resources and may not be suitable for real-time applications [24]. The choice of interpolation method depends on the specific application and the desired balance between accuracy and computational efficiency [24].

2.6 Map Construction

The sensor data acquired by the DHT22 sensor was integrated with the 2D map generated by the SLAM algorithm to create a multi-dimensional map. This was achieved using Matplotlib, a Python plotting library [25, 26]. The temperature and humidity data were interpolated across the 2D map using bilinear interpolation, creating a heatmap representation of the environmental variables, as shown in Figure 4 and Figure 5. The resulting multi-dimensional map provides a visual representation of the spatial distribution of temperature and humidity within the mechanical room.

To ensure accurate alignment between the 2D map generated by SLAM and the heatmap created by the DHT22 sensor, the robot's MPU6050 IMU was utilized. This IMU provides orientation and movement data, enabling precise mapping of the sensor readings onto the 2D map. Specifically, the IMU's accelerometer and gyroscope readings are fused to obtain the robot's gestures and movement, which are then used to transform the sensor data from the robot's local coordinate frame to the global coordinate frame of the SLAM map. Given the temperature and humidity readings happen at one-second intervals, the IMU readings within a second are merged as one data point which aligns to the sensor readings. This alignment process ensures that the temperature and humidity readings are accurately represented in the multi-dimensional map, facilitating a more reliable analysis of the environmental conditions within the confined area. During the plotting stage, those coordinates from IMU readings are connected as a line, representing the path of navigation as shown in Figure **4** and Figure **5**.

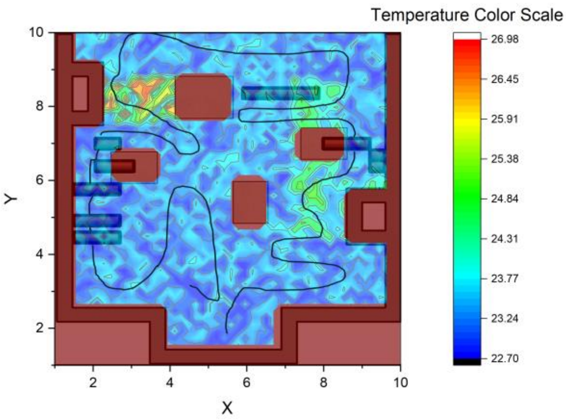

Figure 4 Temperature Heatmap

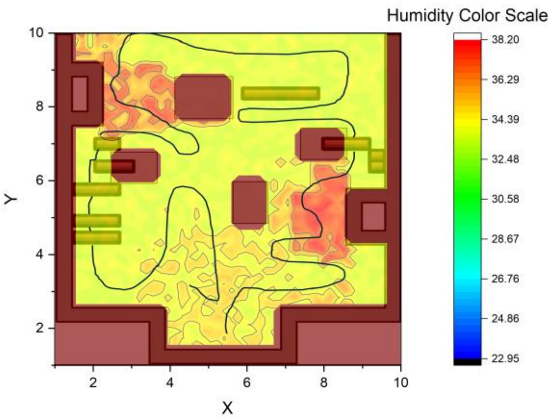

Figure 5 Humidity Heatmap

Due to the limited computational power of the Raspberry Pi, the map construction process for the sensing maps was conducted after the mapping process. The 2D map constructed by SLAM with IMU is used to create a grid for the sensing map. To perform bilinear interpolation and estimate the value at a point $P_{(x,y)}$ on the map, the four nearest grid points, denoted as Q_{11}, Q_{12}, Q_{21}, and Q_{21}, need to be identified. This involves finding the nearest point $P'_{(x\prime,y\prime)}$ on the trajectory curve to $P_{(x,y)}$.

Given the irregular shape of the curve, a piecewise cubic spline interpolation is employed to represent the trajectory. Let $S_{(t)}$ be the cubic spline function that interpolates the robot's path. The nearest point $P'_{(x\prime,y\prime)}$ on the curve to $P_{(x,y)}$ can be found by minimizing the distance:

$$P_{(x,y)} = \min\left(\sqrt{((x - S\_x_{(t)})^2 + ((y - S\_y_{(t)})^2}\right.$$

where $S\_x_{(t)}$ and $S\_y_{(t)}$ are the x and y components of the spline function $S_{(t)}$.

A local coordinate system is then established at P' using the tangent vector and its normal vector at P'. The tangent vector v at P' can be calculated as the derivative of the spline function:

$$v = \left(\frac{dS_x}{dt}, \frac{dS_y}{dt}\right) at\ t = t'$$

The normalized unit tangent vector u and unit normal vector n are then:

$$u = v/|v| = 1, n = \left(\frac{-dS_y}{dt}, \frac{dS_x}{dt}\right)/|v|$$

With a predefined grid spacing h of 0.5 meters, the four nearest grid points Q_{11}, Q_{12}, Q_{21}, and Q_{21} can be determined as:

$$Q_{11} = P' + h * u + h * n$$
$$Q_{12} = P' + h * u - h * n$$
$$Q_{21} = P' - h * u + h * n$$
$$Q_{21} = P' - h * u - h * n$$

The grid spacing h represents the resolution of the sensor data interpolation. A smaller grid spacing results in a finer-grained map with more interpolated points, potentially capturing more detailed variations in temperature and humidity [21]. However, it also increases the computational burden for interpolation. Conversely, a larger grid spacing reduces the computational load but may result in a coarser map that misses subtle environmental variations.

The choice of h = 0.5 meters was based on a balance between map resolution and computational efficiency, considering the limited processing power of the Raspberry Pi. Future work could investigate the effect of different grid spacings on map quality and optimize this parameter based on the specific environment and application requirements.

To provide a more concrete understanding of the system's performance in the bottleneck, the following metrics were collected for the map construction tasks:

Table 1 Performance Metrics

Category	Metrics
CPU Usage	95-97%
RAM Usage	68-70%
Map Generation Time	14 minutes and 37 seconds
Network Bandwidth	5 Mbps

3 Results

This pilot experiment serves as a demonstration of the prototype, which resulted in the successful generation of a multi-dimensional map of the mechanical room, integrating both geometric features and environmental variables. The Cartographer SLAM algorithm successfully mapped the room's layout, including walls, obstacles, and open spaces. The DHT22 sensor collected temperature and humidity data throughout the robot's traversal, which was then overlaid onto the 2D map using bilinear interpolation. The IMU aligned the 2D maps constructed by SLAM and sensors together, resulting in a multi-dimensional map that effectively visualizes the spatial distribution of temperature and humidity within the confined area.

To verify and validate the accuracy of the multi-dimensional map, the robot's sensor readings were compared with manual measurements and observations of the mechanical room along the robot's path. This comparison also ensured that the readings from the DHT 22 sensor were not affected by the heat generated from the robot's motherboard or motors. The SLAM-generated map was verified to represent the room's dimensions and the location of obstacles. These verification and validation steps ensured the reliability and validity of the generated map and the associated sensor data.

The multi-dimensional map reveals that the temperature and humidity levels are not uniform throughout the mechanical room. Areas with higher concentrations of equipment tend to have slightly elevated temperatures, while humidity levels show some variation depending on the proximity to potential sources of moisture or ventilation. The map provides a comprehensive overview of the environmental conditions within the room, highlighting areas of potential concern or interest.

4 Discussion

This research demonstrates the feasibility of integrating sensor data with SLAM by IMU to create multi-dimensional maps using a hexapod robot. The approach offers several advantages, particularly for inspecting confined areas. The robot's ability to traverse complex ground conditions and collect sensor data in hard-to-reach locations makes it a valuable tool for assessing environmental conditions in challenging environments.

However, the research also highlights some challenges and limitations. The limited computational power of the Raspberry Pi poses a constraint on the complexity of the SLAM algorithms. Due to this, the mapping process took a relatively long time, and the multi-dimensional map can only be plotted after the mapping, which shows the weakness for real-time visualization. Moreover, such limited power prevented the authors to utilizing 3D SLAM. Additionally, the accuracy of the multi-dimensional map is dependent on the interpolation method used. While bilinear interpolation provides a reasonable approximation, more sophisticated techniques may be required to achieve higher accuracy, especially in environments with rapidly changing conditions. Meanwhile, the accuracy of values created from the interpolation algorithms should be systematically compare with ground truth maps to ensure the accuracy. Last but the least, the authors acknowledge the limitation that this pilot experiment only serves as a demonstration and the first field test for this robot system approach. More rigorous experimental design is needed to evaluate and improve the capabilities and applications of this system.

Despite these challenges, the potential applications of this research are significant. The ability to map confined areas and identify hazardous conditions has implications for various industries, including disaster response, environmental monitoring, and industrial inspection. Future work will focus on addressing the identified limitations and exploring the use of more advanced sensors and SLAM algorithms to further enhance the accuracy and capabilities of the multi-dimensional mapping approach.

5 Conclusion

This paper presents a method for constructing multi-dimensional maps by integrating sensor data with SLAM by IMU using a hexapod robot. The approach was successfully demonstrated in a confined area, resulting in a map that visualizes the spatial distribution of temperature and humidity. The research highlights the potential of hexapod robots for inspecting hazardous and inaccessible areas, while also identifying challenges related to computational limitations and interpolation accuracy. Future work can focus on addressing these challenges and exploring the use of more advanced sensors and 3D SLAM algorithms with better processing unit to enhance the capabilities of this approach. It is also recommended to evaluate this approach on the efficiency of decision-making.

This research sets the stage for several promising future directions. Firstly, the integration of more advanced sensors with multi-sensing principles, such as gas detectors, will enable the robot to collect a wider range of environmental data, leading to more comprehensive and informative multi-dimensional maps. Secondly, the development and utilization of more robust and computationally efficient SLAM algorithms will improve the accuracy and real-time capabilities of the mapping process, allowing for online visualization and analysis of the environment. Finally, the incorporation of machine learning techniques can automate the identification of anomalies or points of interest within the multi-dimensional map, facilitating decision-making and response in hazardous or inaccessible environments.

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