

Mapping of Multi-Floor Buildings: A Barometric Approach

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Abstract— This paper presents a new method for mapping multi-floor buildings. The method combines laser range sensor for metric mapping and barometric pressure sensor for detecting floor transitions and map segmentation. We exploit the fact that the barometric pressure is a function of the elevation, and it varies between different floors. The method is tested with a real robot in a typical indoor environment, and the results show that physically consistent multi-floor representations are achievable.

I. INTRODUCTION

The problem of simultaneous localization and mapping is one of the most researched topics in robotics. Many methods are proposed to solve the SLAM problem, and it is generally accepted that the problem of mapping indoor environments is well addressed. However, a vast majority of the state-of-the-art methods do not incorporate global constraints, and they only address the problem in 2D. Therefore, mapping of individual floors of a building is considered to be solved, but providing a globally consistent and well-aligned map of the whole building remains as an open question.

In this paper, we aim to tackle this problem using a sensor fusion approach. We exploit the properties of barometric pressure to detect floor transitions of the robot during exploration, and to situate individual floors of the building onto a global coordinate frame.

The major contribution of this paper is a simple, inexpensive and easy-to-implement approach for generating globally consistent maps of multi-floor buildings. Resulting representations can be called as 2.1-dimensional; as the individual floor maps are 2D occupancy-grids and floor elevations are represented as barometric pressures, which are proportional to actual elevation differences between floors.

Our method is built on top of publicly available, and open-source hardware and software frameworks, so that it can be easily implemented on existing systems. We implemented our method into a mobile robot system and evaluated the method in a typical multi-floor building. Results of the experiment prove that the method is capable of generating consistent maps for multi-floor buildings.

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II. RELATED WORK

Mapping of indoor environments is a well-studied problem; several solutions exist for 2D maps and their extension to 3D are emerging. According to Busckha [1], robotic mapping methods fall into 5 categories: metric maps [2], topological maps [3], sensor-level maps [4], appearance-based maps [5] and semantic maps [6]. In this paper, we focus on (metric) occupancy-grid maps, which is one of the most commonly used type of maps in robotics.

Majority of occupancy-grid mapping techniques utilize probabilistic approaches to model robot motion and to represent sensor uncertainties, such as derivations of Kalman filters ([7], [8]), particle filters [9] and graph-based optimization methods [10].

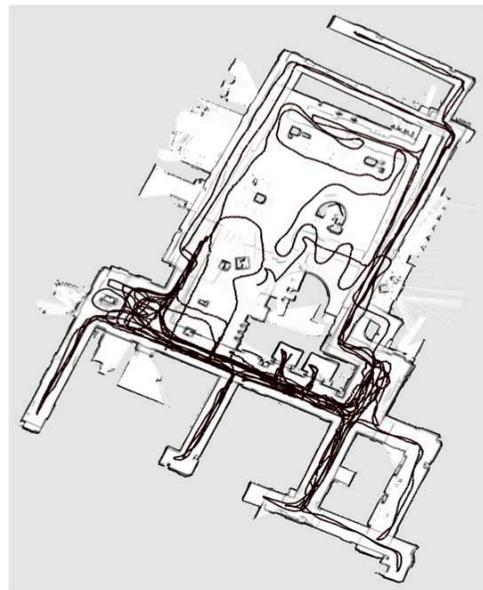


Figure 1, Map of a multi-floor building, as the result of 2D-SLAM: Six floors of the same building are superimposed onto a single plane. The dataset is recorded by a single robot exploring the whole building. The main goal of this work is to segment the map using variations of barometric pressure among different floors.

Despite the number of solutions for 2D mapping, only a few methods deal with mapping of multi-floor buildings. In [11], a visual-odometry based approach is proposed to derive the alignments of floors. In this approach, however, the floors should be mapped sequentially; and salient visual features are required during floor transitions.

SLAM using multiple robots has similar aspects to the problem of mapping multi-floor buildings. In [12], a map-

merging approach is presented to obtain a global map from the individual maps of robots, provided that robots meet with each other during their mission. In [13] this approach is extended in a way that the robots localize each other in their respective maps and create constraints that are used to merge the maps via global localization.

A recently proposed method by Karg et.al. [14] is one of the very few methods that directly address the multi-floor mapping problem. Similar to [13], they use constraints that are derived from global localization to align maps of individual floors. Their method is suitable for multi-robot teams, and it is based on the assumption that certain architectural features of the building are common between different floors. A single sensor modality (laser range finder) is used for global localization and generation of constraints. This method does not perform well if certain architectural features are repetitive, symmetrical or dis-similar in different floors. Moreover, it does not address the issue of which map correspond to which floor of the building, and therefore requires this information has to be manually given.

Morales et.al. [15] demonstrated the use of a barometer for vehicle localization in outdoor woodland environments. Their setup consists of a van that is equipped with wheel encoders, a laser range finder, differential GPS receiver and a high precision barometric sensor. The barometer is used to estimate the altitude in areas where GPS cannot provide reliable information. Last known altitude from GPS is used as the reference point, and the offset is estimated using the barometer.

Our method differs significantly from the above-mentioned methods; both in the way the maps are generated and in the way they are represented. Instead of only providing a correct alignment of the floors, this method also generates a globally consistent representation of the building; which directly correspond to elevations of individual floors, and therefore the actual layout. Furthermore, it does not depend on architectural similarities between different floors, as 2D SLAM is actually sufficient for alignment. On the other hand, our method currently supports single robot systems due to the fact that maps of individual floors are segmented from a continuous, global dataset.

III. METHOD

We combine a laser range sensor and a barometric pressure sensor to align individual maps, detect transitions, and represent floor elevations in a global coordinate frame. Using a laser range finder, we generate 2D-maps of floors and estimate robot path during exploration, and floor transitions are detected using a barometric pressure sensor.

A. Barometric Pressure vs Altitude

Barometric pressure (or atmospheric pressure) is defined as the force per unit area exerted against by the weight of air above that surface in the earth's atmosphere [16]. Therefore,

the change in pressure over an infinitesimal change in altitude should be proportional to the gravitational force exerted by the mass of the air in that infinitesimal layer. This relation can be expressed as:

$$\frac{dP}{dz} = -\rho g \quad (1)$$

where P is pressure, z is altitude, ρ is density of air and g is the gravity. The negative sign denotes the decrease in pressure with increasing altitude.

Furthermore, ideal gas law states

$$P = \rho R T \quad (2)$$

where R is the *Boltzmann* constant and T is the temperature.

Therefore, using (2) and (3), we can write

$$\frac{dP}{dz} = -\frac{g}{RT} P \quad (3)$$

According to the International Standard Atmosphere Model formulated by International Civil Aviation organization [17], zero altitude is measured from mean sea level as

$$P_0 = 101325 \text{ Pa} \quad (4)$$

Therefore, for constant gravitational acceleration and temperature, it is proven that the altitude can be approximated in terms of pressure, using the first order integral of equation (3):

$$z = -\frac{RT}{g} \log\left(\frac{P}{P_0}\right) \quad (5)$$

Our method basically exploits the fact that the barometric pressure decreases as the robot moves to upper floors, and increases as it moves to lower floors. Furthermore, we assume that the pressure remains relatively stable and constant in the same floor, and the pressure difference between the floors is significant between adjacent floors.

To verify these assumptions, the following experiment was conducted. Using a digital barometric pressure sensor, we recorded pressure and temperature from 8 different floors of a typical building. In each floor, data was recorded for the same amount of time (3 minutes), with refresh rate of 1 measurement per second. (Figure 2)

Two observations can be made from this experiment; during short periods (as in floor transitions), pressure remains relatively stable in the same floor, and the pressure difference is significant between floors.

To further prove that the barometric pressure at a static observation point remains relatively same over short periods

of time, we collected temperature and pressure readings from a static point for 5 days (Figure 3). Barometric pressure varies due to atmospheric events, day-night transitions or geographical conditions. Yet, the variations in the barometric pressure happen relatively slowly, as seen in Figure 3. Considering the fact that moving from one floor to another (using elevators) takes at most a few minutes, it can be assumed that the barometric pressure at the respective floors remain the same over the period of transition.

Using these assumptions, the following sections deal with the detection of floor transitions based on barometric pressure changes between floors.

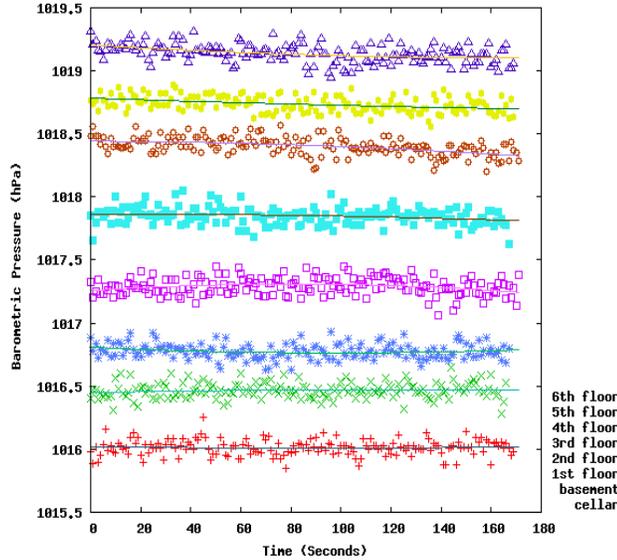


Figure 2, Absolute pressure readings from 8 different floors of a building. Data were recorded asynchronously.

B. Exploration

Our method is developed for a single robot that explores the multi-floor building. During exploration, three types of data are recorded:

- Raw odometry from wheel encoders
- Range readings from laser range finder
- Pressure readings from barometric pressure sensor

At the end of the exploration, we obtain a single dataset that contains time-stamped readings of above-mentioned data.

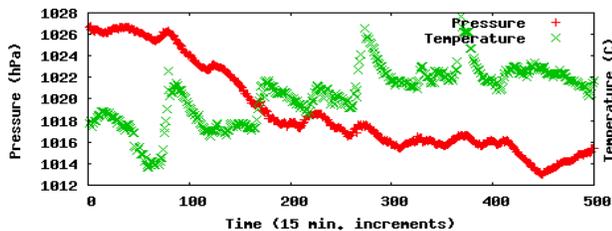


Figure 3, Barometric pressure and temperature over 5 days at a static point. Atmospheric events affects the density of air, hence the barometric pressure.

C. Mapping of individual floors

Based on the state-of-the-art algorithms that address 2D mapping problem, we assume that sufficient solutions exist to generate metric gridmaps of individual floors. Particularly, we adopted the approach of Grisetti et.al. [18] that is based on Rao-Blackwellized particle filters [19], and made available in [20] as an open-source library.

To mention briefly, the key idea of Rao-Blackwellized particle filter for SLAM is to estimate the joint posterior $p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1})$ for the map m and the path $x_{1:t} = x_1, \dots, x_t$ of the robot [19]. Using the observations (range readings) $z_{1:t} = z_1, \dots, z_t$ and the odometry measurements $u_{1:t-1} = u_1, \dots, u_{t-1}$, it is possible to estimate the joint posterior, by using the following factorization:

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1}) = p(m \mid x_{1:t}, z_{1:t}) \cdot p(x_{1:t} \mid z_{1:t}, u_{1:t-1}) \quad (6)$$

Using equation (6), it is possible to first estimate the path of the robot $p(x_{1:t} \mid z_{1:t}, u_{1:t-1})$, and consequently build the map of the environment $p(m \mid x_{1:t}, z_{1:t})$, based on the estimated path.

We use Gmapping [20] to process the dataset and to obtain the corrected robot path based on laser readings. At this point, the whole dataset is processed and it is treated as it is from a single floor rather than a multi-floor environment.

The resulting map is based on the path of the robot, and it is essentially the projection of all floors onto a single plane (As seen in Figure 1).

D. Map segmentation

Map segmentation is the process of dividing the monolithic dataset into segments to represent individual floors. Our method only takes barometric pressure readings into account for map segmentation; and unlike the available methods, repetitive, symmetrical or dissimilar architectural features in the environment do not affect the performance. Segmentation is based on detecting discontinuities of the pressure graph (e.g Figure 4). Raw pressure readings are noisy time series, and for better representation, the raw data is smoothed using Double Exponential Smoothing [21]. The following two equations are associated with Double Exponential Smoothing:

$$\begin{aligned} S_t &= \alpha \cdot y_t + (1 - \alpha) \cdot (S_{t-1} + b_{t-1}) & 0 \leq \alpha \leq 1 \\ b_t &= \gamma \cdot (S_t - S_{t-1}) + (1 - \gamma) \cdot b_{t-1} & 0 \leq \gamma \leq 1 \end{aligned} \quad (7)$$

where α and γ are smoothing constants, y is the raw data, b is the trend of the data and S is the smoothed data. The initial values for the smoothed data and the trend can be taken as $S_1 = y_1$ and $b_1 = y_2 - y_1$ [22].

The detection of floor transitions is based on the rate of change of the smoothed pressure readings. Figure 4 (bottom)

shows the rate of change in pressure, i.e. $\Delta P = |P_t - P_{t-1}|$. Using the mean (μ) and standard deviation (σ), floor transitions are detected at the instants where $\Delta P > \mu + 2\sigma$.

Detecting the segments based on the barometric pressure reveals when the robot travels from one floor to another. Using the timestamps of transitions, the whole dataset is divided into segments of odometry, range and pressure readings from individual floors. We apply SLAM on the segments to generate 2D maps, and we calculate the mean pressure for each floor.

The resulting representation is a globally consistent multi-floor map of the building. It can be referred as a 2.1D map, since the individual floors are represented as 2D metric maps, and the elevations of the floors are represented in terms of pressures.

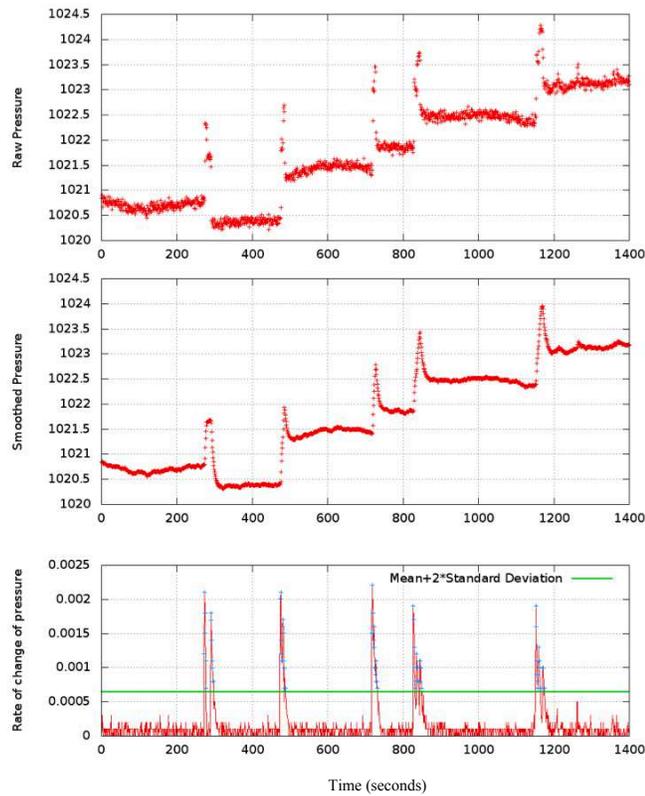


Figure 4, Barometric pressure during exploration. The robot starts its route at the 5th floor, then moves to 6th, 4th, 3rd, 2nd and ground floors. Raw pressure readings (top) are smoothed using Dual Exponential Smoothing (middle). The rate of change of the smoothed pressure reveals the instances for floor transition (bottom).

IV. EVALUATION

A. Environment

We tested the method in a typical multi-floor building using a mobile robot. The experiment took place in Steinman Hall of the City College of New York (Figure 5). The building houses several engineering departments, and it

is mainly consisted of offices, classrooms and laboratories.

During the experiment, the robot explored publicly accessible areas of the building. Office layouts and laboratory arrangements differ significantly between departments and therefore between individual floors.



Figure 5, Steinman Hall - Grove School of Engineering, the City College of New York. Six floors of the building – ground floor to 6th floor– are mapped.

B. Robot platform

The robot used in the experiment consisted of a Pioneer P3AT robot base, a SICK-LMS 200 laser range finder, an SMC1000 barometric pressure sensor and a laptop with Linux operating system. The pressure sensor was interfaced to the laptop through an Arduino microcontroller board, via USB.

C. Exploration

Experiment started at the 5th floor, where the CCNY Robotics Lab is situated. After covering the 5th floor, the robot traveled to 6th, 4th, 3rd, 2nd and 1st floors of the building.

The total length of the path the robot traveled is approximately 927 meters. The overall exploration, including transitions between floors using elevators took 46.4 minutes, resulting in an average speed of 0.33 meters per second.

D. Metric Mapping

We applied Rao-Blackwellized particle filter to the whole dataset using [20]. As a result of the SLAM, the path of the robot and the map are estimated (Figure 1).

Resulting map is the projection of all floors of the building on a plane: A superimposed representation of a 3D environment into a 2D map.

The only commonly covered parts of the individual floors are the main aisles, where the elevators are located. When the robot moves from one floor to another, it observes the main aisles before and after entering elevators.

E. Map Segmentation

In order to segment the map obtained in the previous step, we use barometric pressure data that is recorded during exploration. Figure 4 illustrates the change of barometric pressure among different floors. The exploration starts at the 5th floor, where the Robotics Lab is situated. After covering the 5th floor, robot takes the elevator to the 6th floor, where the pressure is lower as expected. Similarly, the barometric pressure increases as the robot moves to lower floors.

Transition of the robot between floors is clearly observable from the barometric pressure data. The elevator is a closed chamber, where a heating, ventilating and air conditioning (HVAC) unit controls the air circulation inside the cabin. The effect of this phenomenon can be identified as spikes on the graph.

The result of map segmentation process can be seen in Figure 6. Based on the discontinuities of the barometric pressure data; the dataset is segmented into six consecutive parts, and maps of six individual floors are obtained.

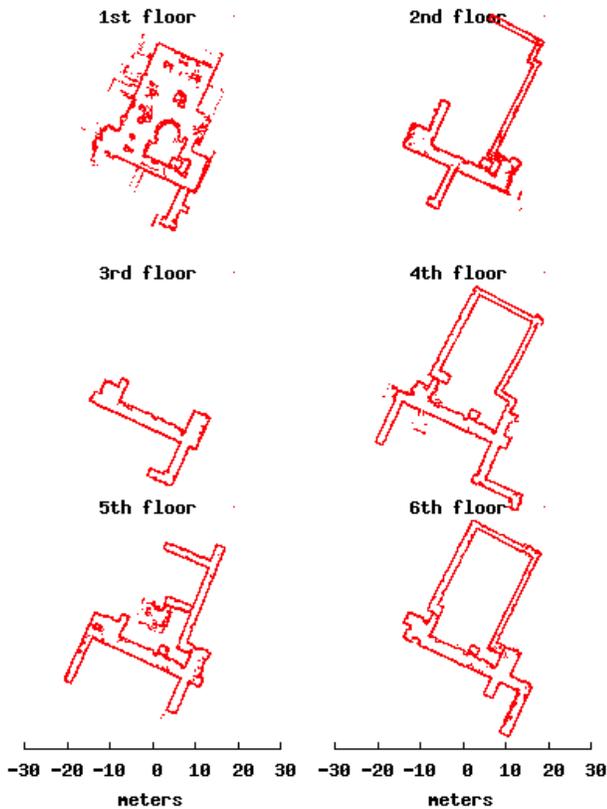


Figure 6, Individual maps of floors. These maps are segmented from the superimposed map in Figure 1, with the help of the barometric pressure log.

As stated previously and illustrated above, the ground floor is a large open space, and the rest of the floors are arranged differently, based on the functional units residing in that floor. The common area in all of the floors is the main aisle, where the elevators are located.

To obtain a physically consistent representation, we directly use the mean barometric pressure for each floor as a measure of elevation. Therefore, 2D layout of the environment is represented as a metric X-Y grid and computed by the SLAM; and the elevation (Z) of the each grid represented by mean barometric pressures that are directly derived from the dataset.

F. Discussion of Results

The results of the experiment are illustrated in Figure 6 and Figure 7; which shows that the method is useful for building physically consistent maps of multi-floor environments.

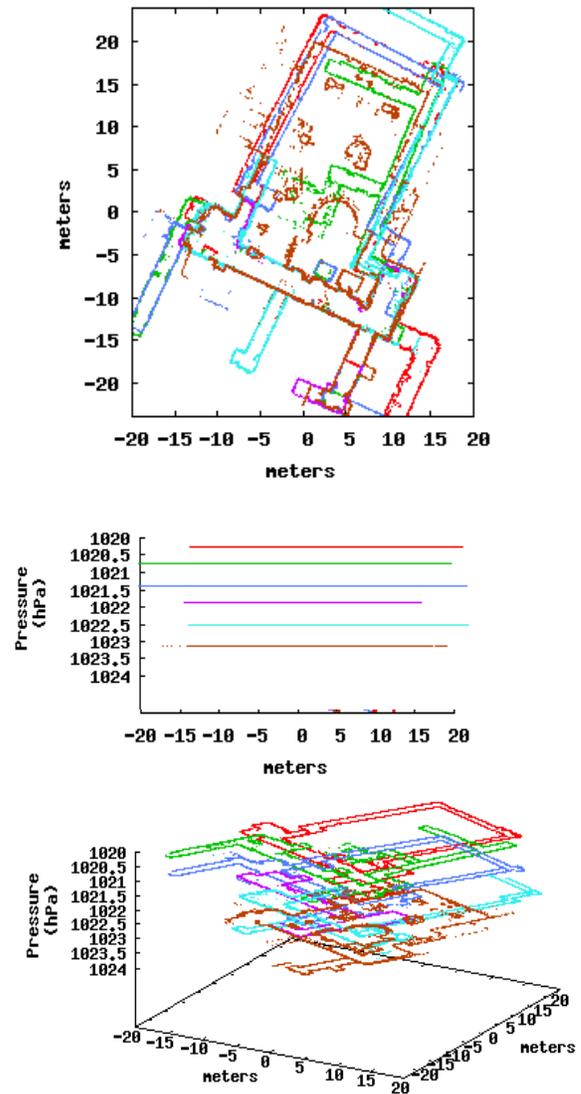


Figure 7, Resulting multi floor map. 2D floor maps are the result of metric SLAM (top). Elevations of individual floors are determined from barometric pressure (middle). The final representation is a 2.5D –sparse 3D-map of the building (bottom). Note the decreasing values of Pressure axis, in order to reflect the physical layout of the building.

The method is based on a set of very simple rules. It uses state-of-the-art metric mapping techniques, and exploits the characteristics of barometric pressure. In contrast to maps generated in [14], where the floor levels are hand-coded into the system; this method is capable of representing the correct order of the floors automatically. Moreover, the elevation differences between floors can also be revealed. From Figure 7 (middle), it is possible to observe that the floors are not evenly spaced. Larger elevation differences between the ground floor, the 2nd floor and the 3rd floor are consistent with the architecture of the building: The ceiling on the ground (1st) floor is significantly higher, and there is a mezzanine floor (2M) between the 2nd and the 3rd floors, which is not explored by the robot.

Metric maps of the individual floors are simply generated by the 2D SLAM algorithm [20]. In general, the maps are consistent and aligned well with the other floors, especially around the main aisle, where the elevators are situated. Due to the shortcomings of the SLAM algorithms, slight misalignments are also detected, as in the map of the 2nd floor (Figure 6). Unlike the 4th floor and the 6th floor, a loop closure is not observed on the 2nd floor; and unlike the ground floor and the 5th floor, the environment is not rich in terms of features. A relatively featureless and long corridor without a loop closure results in poor self-localization of the robot, hence affects the generated floor map.

Figure 7 reveals that the elevations of the individual floors are referenced to the mean barometric pressures recorded at the corresponding floors during exploration. While the relative elevation differences can be represented using mean barometric pressures, they cannot be represented as absolute elevations from mean sea level because of the varying barometric pressure (as seen in Figure 3).

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a novel method for mapping of multi-floor buildings. It is based on laser range measurements to build metric maps of the environment, and barometric pressure measurements to detect floor transitions and segment the metric maps.

The method is tested with a real robot in a typical multi-floor building, and the results show that the method is capable of generating physically consistent maps. It is simple, efficient, and easily applicable to the existing robot systems with an addition of an inexpensive digital barometric sensor.

We aim to extend this framework by tracing the atmospheric pressure changes using stationary sensor nodes placed in the environment. This will allow us to maintain a globally referenced pressure map, and moreover enable mapping with multi-robot systems.

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