Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

Real Time Obstacle Avoidance and Navigation with Mobile Robot via Local Elevation Information

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***Abstract*—This paper considers the real-time navigation and obstacle avoidance of mobile robots in complex environments. A novel local environment perception and navigation framework for mobile robot navigation based on the elevation information is proposed. A local elevation map is introduced to perceive and map obstacles in the local environment. Calculating obstacles' heights and shapes by local elevation maps, the terrain traversability of the surrounding environment of a robot is determined, and a two-dimensional local occupancy grid map for robot path planning and navigation in local environment is generated. The effectiveness of our approach is validated experimentally through real-time navigation and obstacle avoidance in the artificial environment. The experimental results show that using the proposed framework, a mobile robot can safely reach its target position while avoiding the non-crossable area. For indoor mobile robots with limited computing power, in complex environments, it could provides more safe navigation and path-planning.**

***Index Terms*—Mobile Robot, Obstacle Avoidance, Environmental Perception**

I. Introduction

Automated Ground Vehicles (AGV) need to determine the position of obstacles in the environment to navigate themselves safely. However, in a complex environment, there are various obstacles, as shown in Fig. 1. In such an environment, the safe navigation of a robot is a challenge in many applications, such as logistics warehouses or production sites. In many industrial AGV navigation systems, the obstacle avoidance problem is solved by using ultrasonic or 2D Lidar sensors. However, an ultrasonic sensor is not convenient for high-accuracy mapping because it is very sensitive to the noise. Thus, using an ultrasonic sensor, the application can fail to detect structured obstacles is two-dimensional and the information on the obstacle height cannot be perceived, which can cause potential robot collision risk while navigating a robot in complex environments. The RGBD camera is a good choice for obstacle detection in indoor environments where the effective depth value is typically up to 5m. Compared with the Lidar and ultrasonic sensors, the RGBD camera can sense the environment better, providing a more complete and rich information on the local environment.

Fig. 1: The artificially-constructed complex environment.

Currently, the traditional environment mapping approaches can be roughly classified into topological and metric maps [1]. The topological maps represent robot environment in the form of a graph-like structure, where nodes correspond to locations and edges correspond to paths between the locations. This mapping structure is commonly used for path-planning and location tasks in large-scale environments, such as city maps [2]. On the other hand, the metric maps store the geometric environmental properties, which features accurate descriptions of the environment, and hence , obtains either grid-based approximations or geometric primitives to represent the environment. The occupancy grid model proposed by Elfes [4] is one of the most popular metric map techniques. It uses a grid of cells to represent the occupations of obstacles, each of which contains the map-occupancy information of the corresponding location. Therefore, locations in environments can be classified as occupied, unoccupied or unknown.

The occupancy grid map is widely used in robotics, and can be extended to 3D environment mapping through different data structures. Liu et al. [5] proved the reasonableness of the inference of such a method, considering that the data association problem in robotic mapping could be solved by the 3D information on the environment. Namely,

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a 3D occupancy map provides more information and less ambiguity than 2D occupancy map. Despite its advantages, the computing devices of mobile robots usually cannot fully adapt the real-time construction of 3D occupancy grid models. Due to the reason of stability and cost, many industrial mobile robots cannot carry devices with strong computing power. Therefore, these methods are not suitable for direct application in a mobile robot for environment awareness. However, the movement of a mobile robot is always close to the ground. In view of that, a 2.5D elevation grid map seems to be a good alternative. It is an approach for local environment mapping with 3D information using a compact structure named the Occupancy-Elevation Grid.

In most challenging environments, many approaches use 2.5D grid-based elevation maps to sense the environments [6]. In this map, each cell represents the height of the area at a certain corresponding position. While the information on environments in the 2.5D maps has a certain insufficiency, compared to the full-3D maps, they have a more compact structure and better scalability, which ensures efficient data access and amending. Therefore, the traversability of the surrounding environment can be analyzed with some pivotal information on the map.

In this paper, a local environment perception and navigation framework for mobile robots based on the elevation information, which can work more effectively in complex environments using a limited number of sensors, is proposed. To overcome the problem of low computing power of small indoor mobile robots and the corresponding time-consuming obstacle perception and navigation in a complex environment. The rest of the paper is organized as follows. Section II gives a brief overview of the proposed framework. Section III explains how the information on obstacles in the local environment is calculated. Section IV introduces the traversability check principle between the vertical obstacle and inclination obstacles. Section V describes the structure of a local hierarchical planner. Section VI presents the experimental validation of the proposed framework using a real robot. Section VII concludes the paper and provides guidelines for our future work.

II. Overview of Proposed Method

The system overview of the proposed local environment perception and navigation framework is presented in Fig. 2. As presented in Fig. 2, the proposed framework includes three modules, whose functions are respectively detection of local environment, traversability check, and local-path planning and navigation. A brief description of these modules is provided in the following. The module for detection of the local environment builds a local elevation map using the point cloud data acquired by an RGBD sensor. A robot-centric occupy-elevation grid map [7] is used to sense 3D local environment of a robot. As the robot moves, this map is continuously updated, and new data are perceived. For the construction of the elevation map, only the height of local surroundings is needed. The traversability check module calculates both vertical obstacle and slant obstacle values by searching the local elevation map. Two filter functions are used to calculate the vertical and slant values in the local elevation map for each cell, and then these values are mapped to a local obstacle occupancy grid map. The local path planning and navigation module performs the footprint estimation and local path planning. Considering the traversability of the footprint model of a mobile robot in the 2D local obstacle occupancy grid map, the proposed framework allows a mobile robot to avoid local obstacle successfully while following the target path obtained by the global planner. The method described in the following sections was tested in an artificial environment. A real robot and related equipment were used in the experiment.

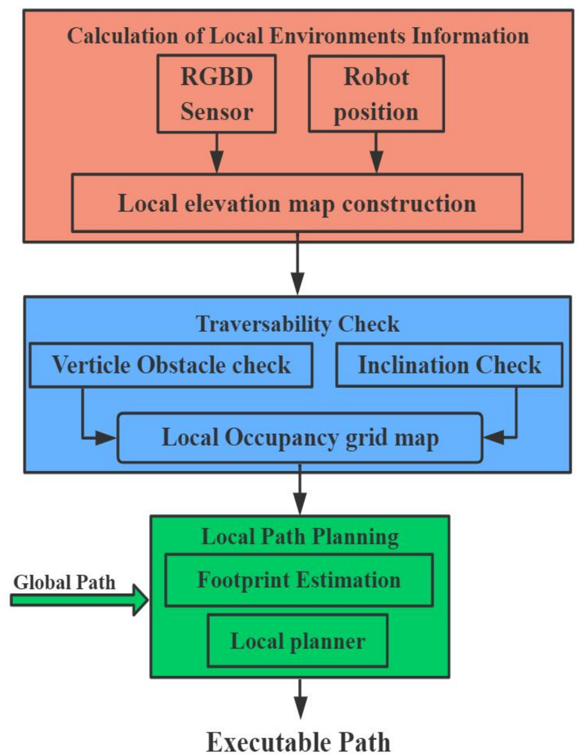


Fig. 2: The flowchart of the proposed framework.

III. Calculation of Local Environments Obstacle Information

The robot-centric elevation map [7] is constructed using the range data acquired by an RGBD sensor. The distance is measured relative to the robot, and when the robot moves, the elevation map updates information about the environment with the robot movement.

Three coordinate frames are defined to describe the pose transformation between the sensor and map. As shown in

Fig. 3, the three coordinate frames, namely the base frame, map frame, and sensor frame are involved in obstacle height estimation. The transformations of the base coordinate frame and sensor coordinate frame are estimated by the robot odometry. The height and position of a point P in the sensor coordinate frame are obtained by the measurement using the sensor data and then converted to the map coordinate frame by transformation.

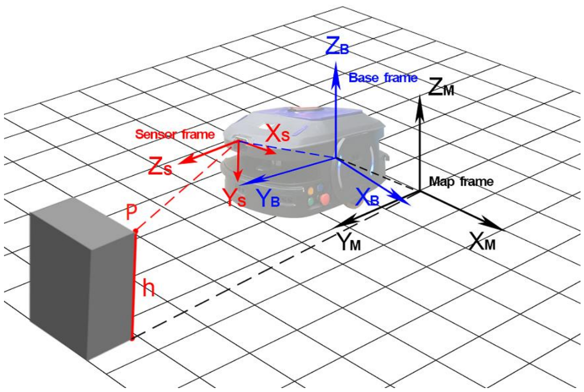


Fig. 3: Schematic diagram of obstacle position calculation using the sensor

The structure of the elevation map data is similar to a two-dimensional occupancy grid [8], where each cell stores an occupancy value, a height value, and variance. The map M can be expressed as:

$$M =< O_{0:t,n}, h_{0:t,n}, \sigma^2_{0:t,n} >, n = 1, ..., N \tag{1}$$

where N represents the number of cells in the grid map. As explained in [9], The above expression can be simplification.The each cell m_n of the map M can be described as:

$$m_n =< O_{0:t}, h_{0:t}, \sigma^2_{0:t} > \tag{2}$$

where $O_{0:t}$ denotes the occupancy value of a cell, $h_{0:t}$ is the estimated height, and $\sigma^2_{0:t}$ represents the variance value of the height. These variables are estimated considering the time accumulation until the time t, and the occupancy and elevation values are computed by the probabilistic functions. The occupancy probability $O_{0:t}$ is given by the probability density function $p(n|s_{0:t}, z_{0:t})$. the historical robot location data $s_{0:t}$, and the historic of sensors readings $z_{0:t}$. The probability $p(n|s_{0:t}, z_{0:t})$ specifies the occupancy probability of m_n conditioned to the sensor data z_t and robot position s_t at time t. The details of the occupancy grid algorithm can be found in [10]. This formulation allows place characterization in an environment that can be classified as occupied or unoccupied by an obstacle.

Elevation values are described by a normal distribution characterized by $h_{0:t}$ and $\sigma^2_{0:t}$, that is,$N(h_{0:t}, \sigma^2_{0:t})$. To address the issues related to the estimation and update of elevation and its variance of each cell, Kalman filter is employed. The Kalman filter considers a new measurement, h_t, with the uncertainty σ^2_t at time t. which are respectively defined by (3) and (4). The more detailed definition of these parameters can be found in [3]. Using Kalman filter, the elevation mean $h_{0:t}$ and its variance $\sigma^2_{0:t}$ of a cell m_n are respectively updated.

$$h_{0:t} = \frac{\sigma^2_t h_{0:t-1} + \sigma^2_{0:t-1} h_t}{\sigma^2_{0:t-1} + \sigma^2_t} \tag{3}$$

$$\sigma^2_{0:t} = \frac{\sigma^2_{0:t-1}\sigma^2_t}{\sigma^2_{0:t-1} + \sigma^2_t} \tag{4}$$

By applying the Kalman filter, the uncertainty of sensor measurement is taken into account. This map is updated with the constant robot movement, and new data are perceived. This method construct an elevation map from a robot-centric perceptive. The data in the map is updated based on the uncertainty of the estimated robot attitude during the robot motion. Thus, the robot can estimate the obstacle height from its local angle at any time.

IV. Traversability Check

The local traversability map is based on the occupancy grid form of the local elevation map, and the traversability analysis of each cell of the local elevation map is performed, including the traversability analysis of both obstacle geometry and footprint of robot. For the purpose of analyzing the traversability of a mobile robot, two calculation rules of traversability estimation are defined, and they are presented in the following subsections.

A. Vertical Obstacle Traversability Check

The vertical obstacle like the high obstacles and tall steps are quite dangerous for mobile robots especially the wheel robots. Because their chassis usually has a limited ground clearance, when the height of the obstacle exceeds the height of their chassis, the traversability of navigation is difficult to guarantee. In order to mark the vertical obstacles that the mobile robot cannot traverse, we traverse the elevation values in each cell of local elevation map.

$$V_{min} = h_{minbase} + \sigma \tag{5}$$

$$V_{trav}(h) = \begin{cases} \frac{V_{min}-h}{V_{min}}, & if \quad h < V_{min} \\ 0, & if \quad h \geq V_{min} \end{cases} \tag{6}$$

In (5), V_{min} denotes the minimum passing height of a robot, and the traversability of every grid above this height will be set to occupied; $h_{minbase}$ denotes the height of chassis ground clearance, and σ denotes the elevation map measurement variance. In (6), $V_{trav}(h)$ denotes the traversability of mobile in vertical obstacles. In addition to expressing the traversability of each grid, it is also needed to express the crossing complexity of the traversable path in a probabilistic manner. Each grid calculated by (6) contains the pass probability of a vertical obstacle. It can indicate the traversability of the robot at different position in front. All $V_{trav}(h)$ values within the footprint have to be traversable; otherwise, it is considered as not traversable.

B. Inclination Traversability Check

For a local environment that corresponds to the footprint size, when the measured inclination exceeds the maximum robot allowed inclination angle, that area is considered as a not-traversable area. The inclination value is calculated using the normal vector of the fitted plane and the direction vector of the vertical-obstacle area. The plane fitting is calculated by using the height information obtained from the local elevation grid map. In order to ensure the effectiveness of the path-planning and safety of navigation, the inclination traversability check will be performed only on the parts that are not considered as vertical obstacles.

C. Local Obstacle Occupancy Grid Map

For the ground-based mobile robots, although it is necessary to perceive 3D obstacles in environment, in the planning stage, the traversal calculations are essentially performed in a 2D space. Namely, the local obstacle occupancy grid map is a 2D traversability representation of obstacles in the local environment of a robot. After analyzing the passability of the local elevation map, a local obstacle occupancy grid map is created, and it describes the distribution of obstacles around the robot at the current moment. The current local traversable information of the robot is used to update the local obstacle occupancy grid map whenever new obstacles are detected in the local elevation map.

V. Local Path Planning and Navigation

The navigation goal is to find a traverse path between the start and target positions of a robot, which can be executed by a path planner. An excellent navigation framework not only searches for the best path from the start position to the target position in the global map but also considers how a robot can avoid obstacles in the local environment effectively and efficiently. The global planner searches for an optimal path to the target point in the global map, while the local planner optimizes the enforceability of the global path, while considering the ergodicity and kinematics of the robot base footprint model in the local map. The update frequency of the local planner is usually higher than that of the global planner. We combine the information of the local elevation map propose a hierarchical planner structure like the above form, but mainly concerned with the generation of local planner paths. The main aim of the proposed framework is to ensure a mobile robot can avoid local obstacles effectively, while following the target path created by the global planner, and we think this framework is the one of best to solve this problem.

A. Footprint Estimation

A clear footprint model of a robot is key to ensure the effectiveness of a traversal search. In most cases, a circumscribed circle that is centered on a robot and covers the inside of the body is usually used as a footprint model of the robot. Representing the footprint with a circle facilitates the estimation of footprint traversability. In this way, the convergence of the cost value can be accelerated, which is especially beneficial for path re-planning using completely or partially the same maps. This guarantees the validity of the path traversing, but it become more conservation. In the actual robot passing of narrow roads containing many obstacles, there will be an insurmountable footprint. Another representation is to use a polygon composed of boundary points around the robot as a robot footprint model. However, in complex environments, only planning using the polygon footprint provides valid paths.

B. Local Navigation Structure

In the navigation module, the path is calculated by the global path planner. The global path planner is provided with the start position (the current robot position) and its target position. The purpose of the global planner is to find a complete global path from the robot start position to its target position using the global map. In general, the global planner can find a cost-effective path in the original map, but in practice, obstacles in a complex environment often cause this path to fail, so following this path may expose robot to the unexpected risks.

In the proposed framework, the global-path segment corresponding to the current robot position is used to perform the traversability check of the currently updated local obstacle occupancy grid map with the configured footprint model. If the segment is valid, the currently executed path will be updated; otherwise, the invalid segment of the global path will be re-planned based on the local obstacle occupancy grid map. If a new valid path segment is found, it will replace the corresponding part of the global path and will be used to update the executed path.

VI. Experimental Results

In order to validate the feasibility of the proposed local obstacle avoidance and navigation framework, an experiment in artificially-created complex environment was conducted. The sample included all kinds of obstacles in a small area, and had a size of 4.0 m $\times$ 4.0 m , as shown in Fig. 4.

The experimental platform was the Biowinbot EM80 mobile robot, which provided a wheeled odometer with an error of less than 1%. Intel Realsense D435 RGBD camera was mounted on the front of the Biowinbot EM80, and it was used to sense the information on the environment in

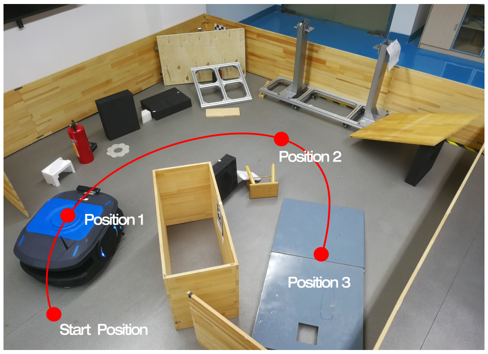


Fig. 4: A complex artificial environment.

front of the robot. The experimental setup is illustrated in Fig. 5. To implement the local elevation mapping and local traversability check, a universal grid map library was used [11].

As mentioned previously, one of the main aims of the proposed framework is to provide a system that can analyze traversability in a complex environment and plan an optimal and feasible path to ensure safe robot navigation in the complex environment. In the experiment, all the results were obtained by using the real data collected by the RGBD sensor.

Fig. 5: Biowinbot EM80 mobile robot with Intel Realsense RGBD camera.

First, the accuracy of the 2D local obstacle occupancy grid map in the description of obstacles in the actual environment, after the travsersability check in the artificially-constructed complex environment, was verified. In the experiment, the values of parameters were as follows. The local elevation map size was 3.8 m × 3.8 m, which was the same as the size of the local obstacle occupancy grid map. As shown in Fig. 4, three locations were selected in the route that the mobile robot passed, and the robot traversability was detected on using the local elevation map at these locations. A 2D local obstacle occupancy grid map was generated by a series of calculation methods presented in Section III.

The experimental mapping result of position 1, position 2, and position 3 (refer to Fig. 4) are shown in Figs. 6(a) and 6(b), Figs. 6(c) and 6(d), and Figs. 6(e) and 6(f), respectively. Meanwhile, along with obstacle avoidance, robot navigation from the start position to position 3 in Fig. 4, was realized at the same time. The entire process was performed in real-time. In the navigation process from the starting position to

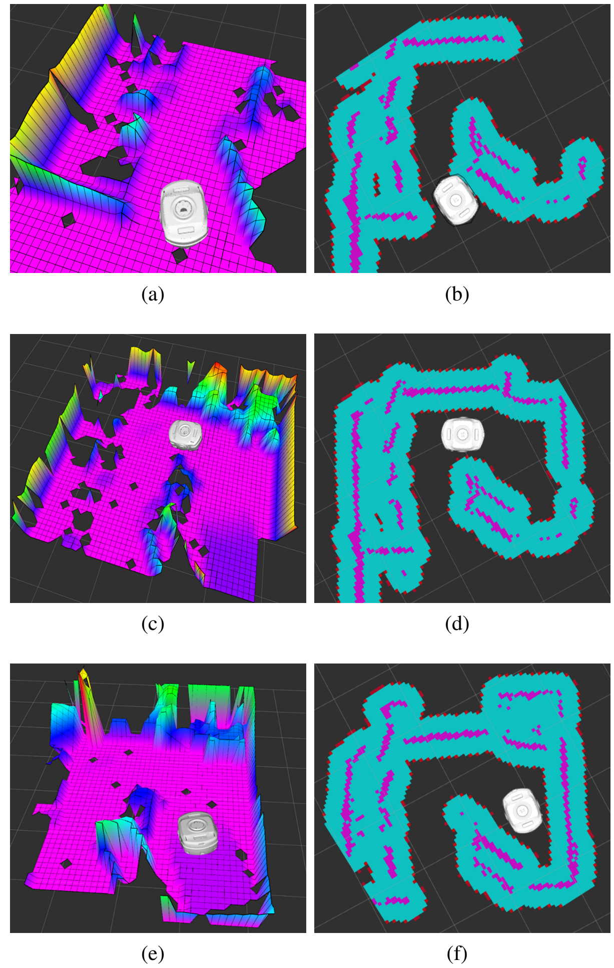


Fig. 6: (a), (c), (e) are mapping estimates of local elevation map and at different locations in a messy environment, (b), (d), (f) are 2D local obstacle occupany grid map generated after traversability check.

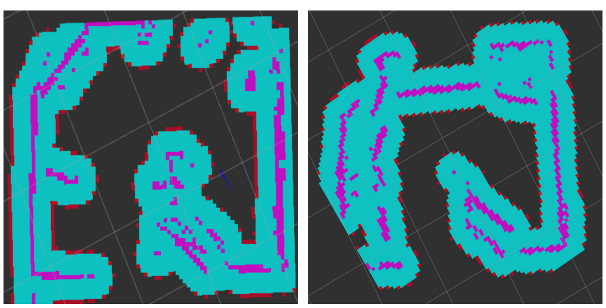
the target position 3, using the local obstacle occupancy grid map generated by our method for local obstacle avoidance planning, the mobile robot could perform the collision-free planning actions in the complex artificial environment, as shown in Fig. 7.

Also, we implemented and tested the method introduced in [12] as a conventional method. During the experiment, we compared the local obstacle occupancy grid maps generated by the two methods. In Fig. 8(a), the result of the conventional method are presented. This approach was less able to describe obstacles of different heights and shapes in the complex environment. On the left side of the map, many high or low ground obstacles in the artificial environment were not well detected. In the upper right corner of the map, a piece of plank obstacle suspended in the air in the real environment was not completely described. As mobile

Fig. 7: The path of collision-free planning from start position to gaol position

robots traversed these obstacles, the probability of collision increased significantly, exposing the robot to a dangerous navigating environment.

The results of our method are shown in Fig. 8(b). Through the traversability check of the local elevation map, the obstacles in the real environment could be well described. Meanwhile, the robot passability was well expressed in the local obstacle occupancy grid map, which greatly increased the probability that the mobile robot could navigate safely in the complex environment. During the experiment, the robot selected a collision-free path in the real environment to follow its way to the target position. The comparison of the proposed method and the conventional method proved the reliability of our method.



(a) (b)

Fig. 8: Comparison of generated local obstacle occupancy grid map: (a)by conventional method and (b)by our method

VII. Conclusion

In this paper, an obstacle avoidance and navigation framework intended for robot navigation in a complex environment is presented. The proposed framework consists of three modules, whose functions are the calculation of local obstacles, traversability check, and local path planning and navigation, respectively. The module for calculation of local obstacles creates a local elevation map from the point cloud data that is acquired by an RGBD sensor. The module for traversability check employs filters to process the obtained local elevation map of the environment and provides information on the vertical dimension and inclination of obstacles in the environment. The planning module generates a local occupancy grid map. The module for local path planning and navigation, considering the traversability of the robot footprint model in the local obstacle occupancy grid map, helps the mobile robot to avoid local obstacles efficiently while following the global target path.

The proposed framework is verified by experiments in the artificially-constructed complex environment. The experimental results verify the reliably of the proposed framework in perceiving and describing obstacles by a two-dimensional local obstacle occupancy grid map in the complex environment. Thus, mobile robots can safely navigate to their target positions while avoiding non-traversable areas in a complex environment.

In our future work, the proposed system stability will be further validated by additional experiments in different complex environments.

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