

Real-time Detection of Dynamic Obstacle Using Laser Radar

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Abstract

Dynamic obstacle detection in unknown environments during mapping is a very essential problem for mobile robots. Dynamic obstacles directly affect the precision of the mobile robot map building. An approach to detecting dynamic obstacles using a 2D laser radar in real-time is proposed in this paper. After filtering out noisy data, sensor readings are mapped into the world coordinate system to build grid map and three consecutive grid maps are maintained. By comparing the state of the same grid cell in the three consecutive grid maps and considering the state of the eight-neighbor cell, static obstacles are identified. Dynamic obstacles then are identified by comparing the current grid map to the already identified static obstacles. The approach has been implemented and validated in real mobile robot MORCS-1. The experimental results have demonstrated that mobile robots can effectively identify dynamic obstacles in unknown environments with good real-time performance and high reliability.

Keywords: *Grid map, map building, dynamic obstacle*

1. Introduction

Dynamic obstacle detection is a basic problem of the mobile robot map building in unknown environments. The fake observations produced by dynamic obstacles affect the accuracy of the map^[1,2,3]. In order to build the accurate and consistent maps, it is very important

to detect the dynamic obstacles and filter them or use them. It is also the problem that must be solved in the process of the mobile robot navigation. Biswas et al. detect changes over time in an environment by map differencing technique which is usually used in the machine vision^[4]. However the method is not of the high reliability. Wolf et al. maintain two occupancy grid maps (One models the static obstacles and the other models the dynamic ones) without considering the localization error and uncertain factors^[5]. In [6], Simultaneous Localization and Mapping (SLAM) and Detecting and Tracking Moving Objects (DATMO) are integrated to solve both problems simultaneously for both indoor and outdoor applications. In [7], Prassler et al. present a concept of Time-Stamp Map which is a projection of range information obtained over a short interval of time onto a two-dimensional grid, where each cell which coincides with a specific range value is assigned a time stamp.

In order to enhance the validity and reliability of the real-time detection of dynamic obstacles in unknown environments, this paper presents a detection method indoor by mobile robot. 2D laser radar is navigation sensor to observe environment. Its observations are projected onto the grid map. The method maintains three sequential grid maps and compares the same cell of them to decide whether it is occupied by static obstacle or dynamic obstacle. Eight-neighbour rolling window is used to deal with the uncertain information. Experimental tests have been performed using mobile robot MORCS-1 made by the Intelligent Centre of Central South University.

2. Dynamic obstacle detection method

2.1. Laser distance measurement

Because laser radar measures distance accurately, it is used as the mobile robot navigation sensor generally. The laser radar LMS291 produced by Sick Corporation and equipped on MORCS-1 is based on the Time-Of-Flight (TOF) measurement principle and has the advantages of high speed, accuracy and anti-jamming.

A pulsed laser beam is emitted and reflected from the object surface. The reflection is registered by the scanner's receiver. The time between the transmission and the reception of the laser beam is used to measure the distance between the scanner and the object. The pulsed laser beam is deflected by an internal rotating mirror turning at 4500 rpm (75 rps) so that a fan-shaped scan is made of the surrounding area.

The distance d of the obstacle equals the half of the product of the light velocity c and the time interval Δt between the beams emitted from the laser and reflected by the obstacle.

$$d = \frac{\Delta t \times c}{2} \quad (1)$$

Here, the velocity of light is 3.0×10^8 m/s.

The angular resolution of LMS291 is selectable at 1° , 0.5° or 0.25° and the data transmission rate can be programmed to be 9.6, 19.2, 38.4 or 500Kbaud. In our research, LMS291 get 361 measurement data throughout the 180° scanning field with 0.5° resolution. With 500Kbaud transmission rate, the scan time of LMS291 is 26.67 ms with communication delay of 3 ms.

Table 1. Measurement error of LMS291

d (cm)	σ_λ (cm)	σ_d (cm)
$d \leq 500$	1.0	3.0
$500 < d \leq 1000$	1.2	3.6
$1000 < d \leq 2000$	1.35	4.05
$2000 < d \leq 4000$	1.7	5.1
$d > 4000$	1.8	5.4

Theoretically speaking, the measurement output of LMS291 is enough to cover the long distance up to 80 m in the cm. mode and up to 8 m in the mm. mode. According to the environment size and the needed accuracy, one of the two modes is chosen. By tests, the values of the standard deviation are obtained in Table 1^[8] to the different distance range. σ_λ is the standard deviation of the observations in static environment, whereas σ_d is used in dynamic environment. But, the laser information is still local and sparse relative to the vision, and it will be affected by the range and the angular interval in measuring.

2.2. Grid map building

The working environment of mobile robot is described by 2D Cartesian grids in this paper. We take a 2D array as the environment map model and an array value is the states of the corresponding grid cell. It assumed that each grid cell is only one of two states, **empty** or **occupied**, and that has to be estimated from sensor observations.

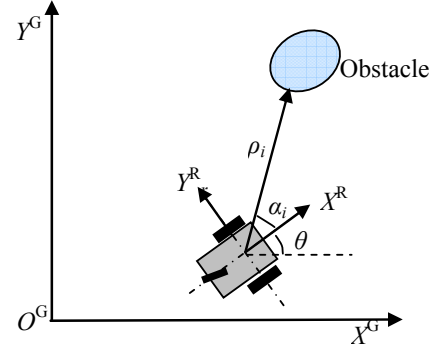


Fig.1. Measurements transformed into global reference frame

Observations should be transformed into the global reference frame as Fig.1 in order to detect the dynamic obstacles in time-varying environment.

We refer to (ρ_i, α_i) ($i=1, \dots, 361$) as the scan pose in the robot reference frame, where i is the number of scanning data of LMS291; ρ_i is the distance from the laser radar to the i -th obstacle; $\alpha_i = i \times 0.5^\circ$ is the angle of the i -th laser beam relative to the robot reference X^R orientation. The conversion from the scan pose to global Cartesian coordinate system is written in equation (2).

$$\begin{cases} x_g = x_r + \rho \times \cos(\alpha + \theta) \\ y_g = y_r + \rho \times \sin(\alpha + \theta) \end{cases} \quad (2)$$

where, (x_g, y_g) represents the coordinate of the i -th obstacle in the global coordinate system; (x_r, y_r) is the current center coordinates of mobile robot in the global coordinate system (assuming that the center of the laser radar is at the center of the mobile robot). Then the project from the coordinate of obstacles in the global coordinate system to the corresponding grid cell in the local map is written by equation (3)^[9].

$$\begin{cases} x_{gm} = \text{int}(x_g / w) \cdot w + \text{int}(w / 2) \\ y_{gm} = \text{int}(y_g / w) \cdot w + \text{int}(w / 2) \end{cases} \quad (3)$$

Where, (x_{gm}, y_{gm}) is the project coordinate of obstacles in the local grid map, and w is the grid width. Thus the local map is built by occupancy grid.

2.3. Dynamic obstacle detection

A grid map represents environment by means of a two dimensional evenly-spaced cell $c_{i,j}$. Each grid cell estimates the probability of the corresponding region being an **occupied** ($c_{i,j}=1$) or **empty** ($c_{i,j}=0$) space area in the environment.

It is very convenient and direct to describe the distribution of the obstacles especially in the indoor environment by mapping the observations in the grids real time. However, the laser radar alone can not tell the kind of the obstacles. The history information is needed to help decide whether the cell is occupied by dynamic or static obstacle. In this paper, by differencing three consecutive grid maps the dynamic obstacles are detected.

Order the grid map at time t as M_t . Then M_{t-1} is the grid map at time $t-1$ and M_{t+1} at time $t+1$. If the states of the same cell $c_{i,j}$ in M_{t-1} , M_t and M_{t+1} are all occupied, the cell is occupied by static obstacle, or else by dynamic obstacles potentially. Fig.2 shows an example of the dynamic obstacles detection by three OGM.

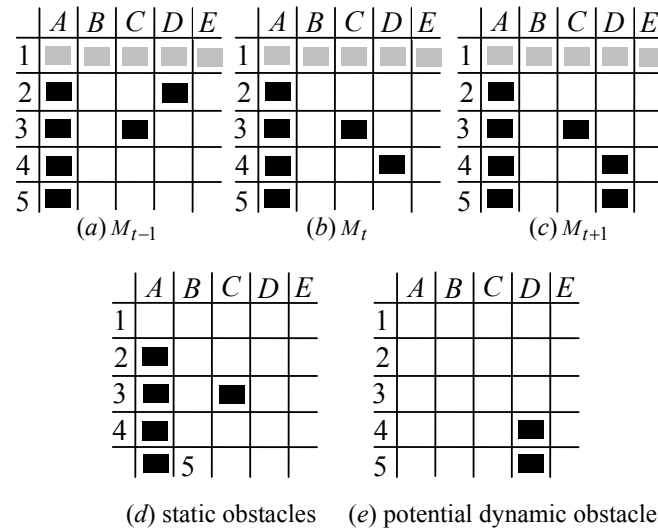


Figure 2. Real-time detection of dynamic obstacles based on maintaining grid maps

In Fig.2, the grey space in the grid represents an unknown region, the black space represents an occupied region, and the white space represents an empty (or free) region. The cell C3 is black in M_{t-1} , M_t and M_{t+1} , which means that at three consecutive time the obstacle is observed still by laser radar in the same region. The cell D2 is black in M_{t-1} but white in M_t and M_{t+1} , which means the region corresponding to the cell D2 is occupied by a potential dynamic obstacle (a dynamic obstacle or a new static obstacle). In the same way, the cell D4 and D5 are also potential dynamic obstacles. Fig.2 (d) and (e) are static and potential

dynamic obstacles respectively resulting from the difference of the three consecutive grid maps.

Potential dynamic obstacles are identified by comparing the current grid map and the map of already identified static obstacles. Then after one more scan period the dynamic obstacles or the new static obstacles can be distinguished from the potential dynamic obstacles.

2.4. Uncertainty treatment

In the process of the mobile robot mapping there are many uncertain factors from laser radar measurement, coordinates transformation, dead-reckoning localization and et al. The same static obstacle observed by laser radar would not always at the same cell in the grid map because of the uncertainty. Therefore, it is very important to take the uncertainty into account.

If a cell is black in M_{t-1} and M_t but white in M_{t+1} , the obstacle at this cell maybe static. By analyzing the observations during the mobile robot movement, the angles measured at the consecutive time are of high relativity. The angles of the neighbour scans at one time are relative high too [8]. The spatiotemporal relativity of the laser radar measurements could help the reliability and validity of the dynamic obstacles detection. Here the eight-neighbour cells are considered. In other words, the eight-neighbour cells should be considered before the cell $c_{i,j}$ is going to be determined static. The eight-neighbour cells are written as

$$\begin{matrix} c_{i-1,j-1} & c_{i-1,j} & c_{i-1,j+1} \\ c_{i,j-1} & c_{i,j} & c_{i,j+1} \\ c_{i+1,j-1} & c_{i+1,j} & c_{i+1,j+1} \end{matrix}$$

If the values of the cell $c_{i,j}$ in three consecutive grid maps are consistent as 1 (Black) and $c_{i+m,j+n}=1$ ($m, n = -1, 0, 1$; m and n would not equal 0 at the same time), the cell $c_{i,j}$ is occupied by static obstacle. The simple treatment to the uncertainty enhances the capability of the static obstacle detection and the reliability of the dynamic obstacle detection.

3. Experimental results

In order to validate the ideas presented in this paper, experimental tests have been performed using MORCS-1. The size of MORCS-1 is 800 mm \times 700 mm \times 900 mm with four drive wheels and an omni-directional wheel as Fig.3.



Fig.3. Mobile robot MORCS-1

In the experiment, we use cm. mode and set the frequency as 20 Hz, the angular resolution as 0.5° . LMS291 is in serial communication with mobile robot control computer by RS422 protocol with 500 Kbaud communication rate. One cell corresponds to $5\text{ cm} \times 5\text{ cm}$ region in real environment. The grid maps are set 800×600 . All of the experiments are performed in the office and peoples are walking come and go as dynamic obstacles. The mobile robot MORCS-1 navigates in an unknown dynamic environment and localizes by dead-reckoning assuming that the localization error is neglectable in a short time.

3.1. Detection when mobile robot still

In this experiment, MORCS is still to detect the dynamic obstacles in an office room with $10\text{ m} \times 12\text{ m}$ size. The walking speed of the people is about 100 cm/s . When the 26th group of LMS291 observations are processed, the detecting result is as Fig.4.

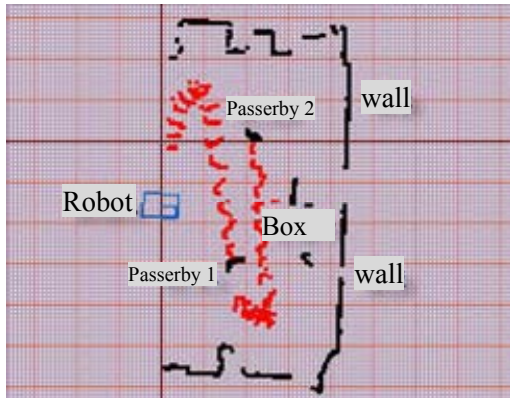


Fig.4. Real-time detection when mobile robot is still

In Fig.4, there are two passersby and two still boxes in the room. The blue rectangle represents the robot; black grids are static obstacles and red grids are dynamic obstacles. From the result, we can see the

static and dynamic obstacles are detected available. The tracks of Passerby 1 and Passerby 2 are continuous. But the wall is ruptured because the passersby and the boxes blocked the laser beams, which is unavoidable when mobile robot is still. We test 24 times, the average detection time is 30 ms and the dynamic obstacle detection is 97.6%.

3.2. Detection when mobile robot moving

The first set of the experiments is implemented at the corridor with the size of $12\text{ m} \times 2.4\text{ m}$. The speed of the robot is 10 cm/s , and the speed of the passersby is about 40 cm/s . 60 sets of the returns from LMS291 are processed during the mobile robot navigation.

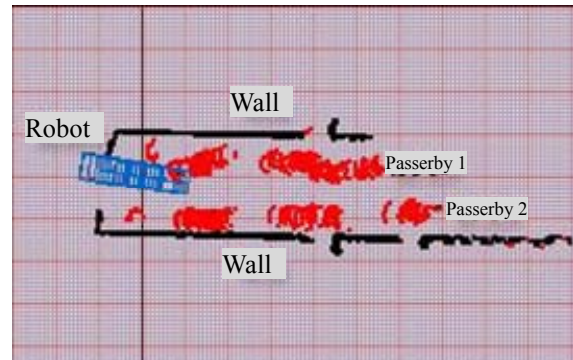


Fig.5. Real-time detection in the corridor when mobile robot is moving

Mobile robot detects the dynamic obstacles real-time in the corridor as Fig.5. The above and below red tracks are Passerby 1 and Passerby 2 respectively. The direction of the passersby and the mobile robot is just opposite. However the tracks of the passersby are not continuous because of the discontinuity of the communication which results from the disturbances in the environment and the limits of the facility. And there are some static points detected as dynamic ones (some red appearing at the black wall). These errors are occurred with the uncertainties. We test 30 times, and the average detection time is 35 ms and 95.4% the right dynamic obstacles are detected.

The second set of the experiments is implemented in the room with the size of $7.5\text{ m} \times 7.2\text{ m}$. There are some pieces of furniture which complicate the robot working environment. The speed of the robot is 15 cm/s , and the speed of the passersby is about 50 cm/s . Passerby 1 and Passerby 2 are walking across towards the mobile robot from the above and the below corner respectively. 70 sets of data are returned. As Fig.6, the method accurately detects not only the passersby as dynamic obstacles but also the wall and the desks and the chairs as static obstacles. There is some detection leaved out in some scan period due to the

communication delay. The experiment is tested 20 times, and the average detection time is 32 ms and 94.8% the right dynamic obstacles are detected.

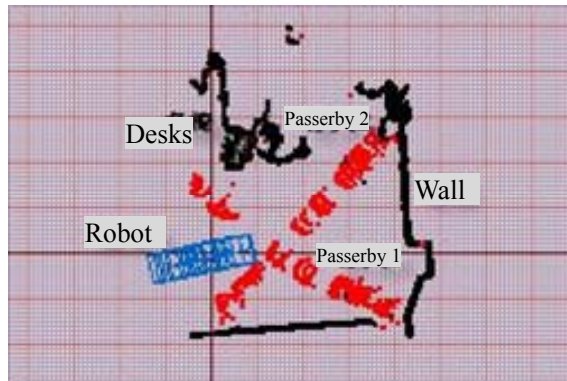


Fig.6. Real-time detection in the room when mobile robot is moving

4. Conclusions

In this paper, we introduced a real-time dynamic obstacle detection approach of the mobile robot based on maintaining three grid maps. The method considers not only temporal but also spatial factors to detect the state of the obstacles, which improves the reliability of the map.

It is worth notice that the mobile robot localization directly affects the map accuracy^[10]. If used in the long journey the dead reckoning will accumulate the excursion error. Thereby the advance methods such as Markov^[11] or Particle Filters^[12] should be adopted in the localization. And if used in the large scale outdoor environments, the grid method will be hard to perform real time. In order to improve the veracity of the detection, the information fusion of the laser and the vision will take into account in the next step research.

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