Directional Grid Based Map Building Algorithm for Mobile Robot

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Abstract – **In this paper, we report an enhanced grid-based map-building methodology. The proposed algorithm is an improvement over traditional grid-based map-building algorithms since the information obtained from the sensors posture and grid cells probability in each measurement are utilized. The proposed algorithm is evaluated by simulation as well as experiments. The results indicate that the proposed algorithm is better than the traditional algorithms especially in highly un-constructed indoor environment.**

I. INTRODUCTION

One of the important tasks to be performed by a mobile robot is to understand the environment from sensor readings. Historically, different approaches have been used in the robotics literature. Grid-based models, also known as occupancy grids, use a 2D array to represent the environment. Each cell, usually square-shaped, is used to represent free space, occupied space or unknown space. This low-level grid-based approach proves to be very useful for map building using sonar sensors [1-3]. Grid-based maps are considerably easier to learn, partly because they facilitate accurate localization and partly because they are easy to maintain.

Sonar sensors provide a relatively low-cost range measurement device for robot applications. The principle of operation is based on measuring the time difference between a packet of transmitted ultrasonic waves and the detected echoes (the details of operation of the Polaroid ultrasonic sensor can be found in [4]). Moreover, the beam angle will be considered as 12.5° from the primary axis of the sensor [7,8]. Therefore, if multiple reflections of the range data are not taken into account, the use of probability distribution function [6-8] for modeling the 25° radiation cone provides a fairly accurate method to represent the angular and radial uncertainty of the sonar data. However, sonar sensor suffers from several severe problems, such as poor angular resolution, specular reflection, crosstalk, etc. In order to provide better accuracy for the sonar measurements, various modelling techniques have been proposed. Kuc and Siegel [9] proposed a widely used sonar sensor model to model the sensor impulse response. Barshan and Kuc [10] proposed to use a two-transducer system to differentiate the difference between the sonar reflections generated by corner and plane according to amplitude and range values as functions of inclination angle. However, it requires relatively complicated hardware setup. Thrun [11] used the back propagation training method applied to an artificial neural network to map number of sonar measurements to occupancy values. They claimed that their approach could easily be adapted to new circumstances and multiple sensor readings were interpreted simultaneously. Jörg and Berg [12] proposed pseudo-random sequences together with a matched filter receiver to reduce the crosstalk generated by a set of sonar sensor operating simultaneously. However, it may cease to operate if there is any irregularity on the detected object. Harris and Recce [13] performed a quantitative test on the sonar data for various orientations and distances between the wall and the sensor. Gutierrez-Osuna and Janet [14] proposed probabilistic model of sonar sensors using back-propagation neural networks trained from experimental data that captured the multi-lobal pattern generated by sonar sensors due to specular reflection. However, it required a rather complicated set-up and the neural network had to be re-trained if the irregularity of the surface was different from the training phase and service.

In this paper, a novel approach on integrating the benefit of occupancy grid based map and metric map approach is reported. The orientation of the sensors during making measurement will be used to enhance the accuracy of the occupancy grid cells. The state of each cell in the grid map will not be only represented by a probability value (i.e. the cell is being occupied), but also the grid cell estimated direction will be updated for each grid cell.

This paper is organized as follows: In Section 2, the complete implementation of the directional grid map will be discussed. Section 3 will show the result of the proposed method and the paper will be concluded in Section 4.

II. DIRECTIONAL GRID BASED MAP BUILDING ALGORITHM

The traditional grid-based map building algorithms use single probability value for each grid cell in order to represent the occupancy of particular location. In this paper, instead of using single probability value, a three dimensional vector is used to represent the probability of particular cells as being occupied as well as the direction of the grid cell. The proposed algorithm is summarized in the following sections.

A. DIRECTIONAL GRID CELL (DGC)

Each cell in the directional probability grid map contains a Directional Vector (DV) which is formed by two values namely occupancy value p_{occ} and estimated direction p_d . The p_{occ} represents the possibility of a particular cell being occupied or not and it just like the traditional approach [1] whereas the p_d represents the direction of the grid cell. The DV can be visualized by a 3D vector as depicted in Figure 1.

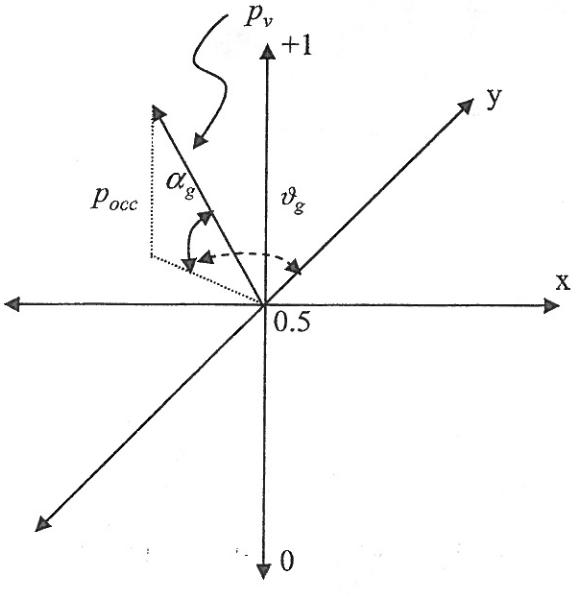


Fig. 1 A 3D vector model for the Directional Probability Vector (DPV) p_v.

In Figure 1, the vertical axis represents the possibility value p_{occ} of the DGC, the angle between the vector and the x-y plan is the grid cell orientation α_g, and the horizontal axis (i.e. x and y) constitutes the estimated direction ϑ_g of the DGC. The length of the DV will be always equal to 0.5 so that the $p_{occ} \in \{0,1\}$ since the DV is pivoted at 0.5 along the z-axis.

The estimated direction will be used to tune the probability distribution function *pdf* of the sonar sensors and it will be discussed in the next section.

B. UPDATE RULES FOR THE DPGC MAP

The *pdf* for each sonar measurement will be used to integrate with the DGC in each sampling interval. The *pdf* will be chosen as the zero-mean Gaussian Probability Distribution function and it is depicted in Figure 2. The *p.d.f.* that is used to model the occupancy probability of the range reading of the sonar sensor is as follows:

If $0 \le x < a$ and $(1-k_\varepsilon)\exp\left(\frac{-(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right) > 0.5$ then

$$p(r \mid z, \bar{\theta}) = 1 - (1-k_\varepsilon)\exp\left(\frac{-(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right) \qquad (1)$$

If $a \le x < b$ and

$$(1-k_o \exp\left(\frac{-(r-z)^2}{\sigma_r^{\ 2}}\right))\exp\left(\frac{-(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right) > 0.5 \text{ then}$$

$$p(r \mid z, \bar{\theta}) = 1 - (1-k_o \exp\left(\frac{-(r-z)^2}{\sigma_r^{\ 2}}\right))\exp\left(\frac{-(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right) \qquad (2)$$

If $b \le x < c$ and

$$k_o \exp\left(-\left(\frac{(r-z)^2}{\sigma_r^{\ 2}} + \frac{(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right)\right) > 0.5 \text{ then}$$

$$p(r \mid z, \bar{\theta}) = k_o \exp\left(-\left(\frac{(r-z)^2}{\sigma_r^{\ 2}} + \frac{(\theta-\bar{\theta})^2}{\sigma_\theta^{\ 2}}\right)\right) \qquad (3)$$

Otherwise,

$$p(r \mid z, \bar{\theta}) = 0.5$$

where θ is the azimuthal angle measured with respect to the beam central axis.

$\bar{\theta}$ is the mean azimuthal angle measured with respect to the beam central axis.

$\sigma_\theta^{\ 2}$ is the variance of the angular probability.

x is the distance that away from the sensor

$\sigma_r^{\ 2}$ is the variance.

m_r is the maximum range of the sonar sensor.

r is the sensor range measurement of the sonar sensor

z is the true parameter space range value.

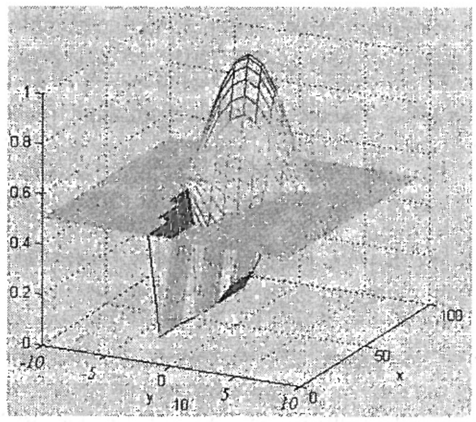


Fig. 2 Gaussian Probability Distribution Function of Sonar sensor.

The estimated angle ϑ_s and grid cell orientation α_s obtained from each sonar measurement is depicted in Figure 3.

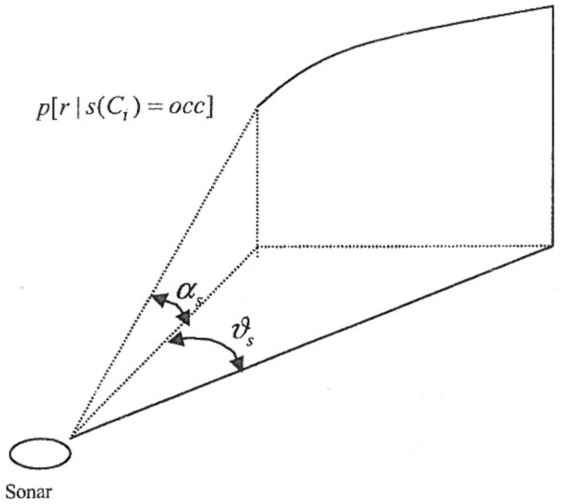


Fig. 3 The sensor's probability angle α_s and estimate direction ϑ_s extracted from the *pdf.*

The update rule for each DGC in the DGC map is summarized as follows:

$$\alpha_s = \sin^{-1}(p[r \mid s(C_i) = occ]) \tag{4}$$

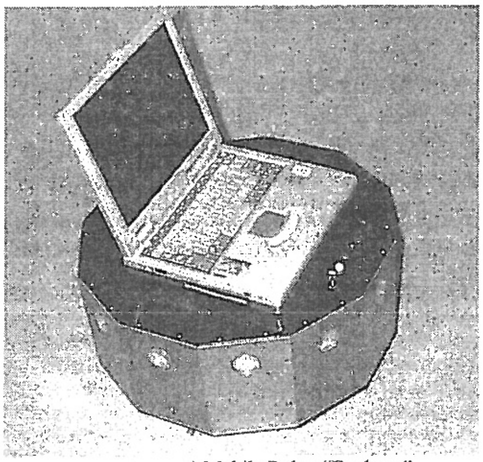
$$\alpha_g' = \alpha_g + (\alpha_s - \alpha_g)(1 - \frac{|\vartheta_g - \vartheta_s|}{180}) \tag{5}$$

$$\vartheta_g' = \vartheta_g + (\vartheta_s - \vartheta_g)\alpha_s \tag{6}$$

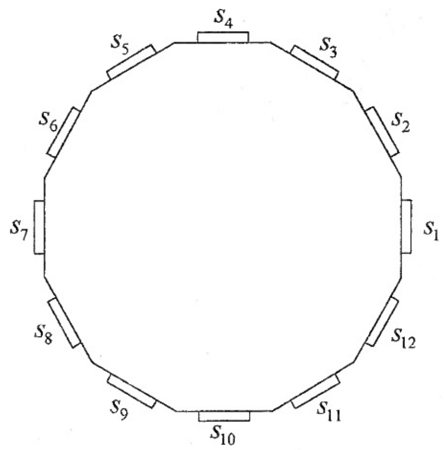
In each sonar measurement, the probability value of particular cell C_i from sonar sensor r will be $p[r \mid s(C_i) = occ]$ and it will be used to calculate α_s. The updated grid cell orientation α_g' and estimated direction ϑ_g' will be updated by Equation (5) and (6) respectively.

III. RESULTS

The test platform of the proposed algorithm was an in-house-built mobile robot "Explorer" (Figure 4). The weight of the robot is 20 pounds and can carry a payload as heavy as 15lbs. The driving mechanism of the robot consists of two dc reversible motors with dead reckoning and 2 castor wheels. The perception system of the robot consists of 12 Polaroid ultrasonic ranging sensors, evenly distributed around the robot, to provide object detection and ranging information to the on-board 11.0592MHz Intel 89c52 micro-controller. The maximum detected range of the sensor is 3 meters (i.e. $m_r = 3m$) and the maximum data acquisition rate is 4.3/sec/sensor. The sensory information and control variable can transfer to the supervisory computer via RS-232 for remote monitoring and control. The robot is powered by a single 12VDC 16Ah sealed lead acid cell, which provides about 5 hours run per charge.



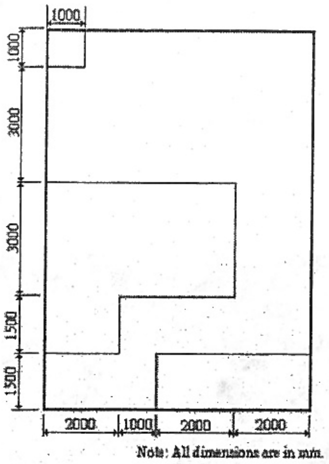
a) Mobile Robot "Explorer"



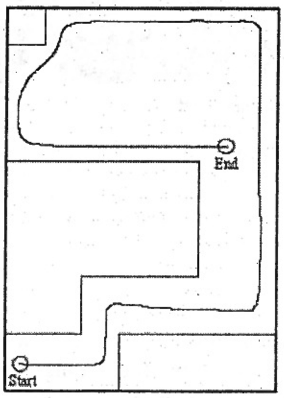
b) Sensors' location.

Fig. 4 Experimental setup

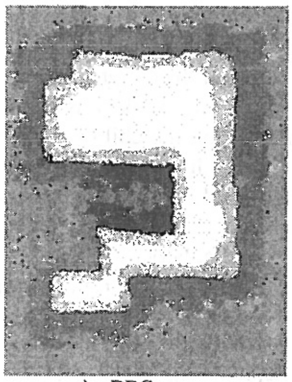
The robot is driven to move in the pre-defined path for modelling the environment as shown in Figure 5a. The robot path as well as the DGB map using the proposed algorithm are shown in Figure 5b and Figure 5c respectively. In both of the experiments, the size of grid cell is 5cm x 5cm and the robot is controlled remotely from the host computer. Moreover, unlike the traditional approach that the input range reading need to be threshold, the robot uses the maximum range reading (i.e. $m_r = 3m$) throughout the whole experiment. In Figure 5c, we can see that the proposed algorithm can provide a clear grid based map. Moreover, one can see that the grid cells which were scanned by the sensors in opposite directions can obtain with high probability of occupancy (e.g. middle of Figure 5c) whereas the grid cells which were scanned by the sensors in one direction only obtain relatively lower probability of occupancy. Unlike the traditional approach [1], the proposed algorithm can give the idea of the feature of the modelled environment since the probability of particular grid cell can not approach 1 (i.e. around 0.7) means the environment is not fully explored or it is a thick wall. On the other hand, if the probability of particular grid cell approaches 1, the environment which is being modelled is a thin wall.



a) The environment being model



b) The robot path



c) DBG map

Fig. 5 Experimental result

IV. CONCLUSION AND FUTURE WORK

In this paper, a novel grid based map building algorithm is reported. Unlike the traditional probability grid based map building methods in which the occupancy of the environment is modeled by only a probability of grid cells, the proposed algorithm shows that the environment can be modeled by a grid cell that combine the directional information and probability of occupancy. Experiment shows that the proposed algorithm can also give a clear and relatively lower computational cost method to obtain a grid based map. The directional information of the DGB map will be used for path planning in the future research works since it gives indication of an area being fully or partially explored.

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