Obstacle Detection in Mobile Robots Using Sonar Data*

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RESUMO
Para possibilitar o alargamento do campo de aplicações de um robot móvel, é necessário considerar a existência de obstáculos transitórios, ou seja, obstáculos que não constem de qualquer mapa fornecido a priori. Neste artigo é descrito um método de detecção de obstáculos, baseado na construção de imagens a partir de dados fornecidos por sensores de ultra sons. Este trabalho tem vindo a ser desenvolvido no âmbito do projecto PO-ROBOT[1].

1 INTRODUCTION
PO-ROBOT is an autonomous system that is being developed on a Robuter platform. The objective is to provide it with basic navigation functions. The sensors used are a ring of 24 sonar sensors and encoders coupled with the driving wheels providing odometric information.

Those navigation functions could be based on one of the following approaches:

- No environment description is given so the robot must use sensorial information to build it on line.

- The environment is static and its description is given.

- The environment description is given but unexpected objects can be found.

For a mobile system to operate in a human populated environment it must have the ability to overcome unknown a priori obstacles[7]. In our case, we follow the third approach, because the robot localization is estimated[6] by matching the sonar readings with the a priori map and the presence of unexpected obstacles is considered.

In this paper we describe the PO-ROBOT obstacle detection module that is being developed.

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ABSTRACT
In order to increase the range of applications of a mobile robot, it is necessary to consider the existence of transient obstacles, i.e. objects not represented in some a priori map. This paper describes a method of obstacle detection based on the incremental construction of images from sonar data. This work is integrated in the PO-ROBOT project[1].

![Figure 1: The range measure R could be produced by either of the targets represented.](image)

2 ENVIRONMENT INFORMATION FROM SONAR RANGE DATA
The amount of information that can be obtained from the time of flight of an ultrasonic wave, is very limited and subject to errors. One echo return only gives the information that somewhere within the beam width at a distance R from the sensor, there is a point that produced the echo.

As can be seen on figure 1, the echo could virtually be produced by any object, at a distance R from the sonar sensor, that falls inside the scanning region (i.e. inside the sonar opening angle).
Figure 2: Probability distribution of range readings given a target (sensor is at the left corner)

This leads us to consider the arc A1 as a region of constant depth (RCD)[3], i.e. a set of points which are equally candidates to be considered as the one that produced the echo.

Experimental results[5] have shown that standard deviations of range errors are upper-bounded by

$$\sigma_D(r) = 0.00052 \times r + 0.002 [m].$$  \hspace{1cm} (1)

where $r$ is the distance between the sensor and the target in meters.

Using this we can consider that the sonar sensor range measures are corrupted with Gaussian noise of zero mean and variance $\sigma^2$ [4]. Then, the following expression gives the probability of obtaining a sonar reading of value $r$ for a target at a distance $z$.

$$p(r|z) = \frac{1}{\sqrt{2\pi} \sigma} \exp \left( -\frac{(r-z)^2}{2\sigma^2} \right)$$ \hspace{1cm} (2)

This can also be seen on figure 2.

3 WORKSPACE AND OBSTACLES

The localization and characterization of obstacles that can be present in the robot’s workspace, can not be achieved by performing a single sonar reading, even if we are using an array of sensors. For obstacles located far away from the sensor it is even worse, because the length of the RCD grows with distance and with it, its uncertainty.

Figure 3 illustrates this situation: the target produces echo returns for both sensors 1 and 2 but one cannot tell whether it was a single point common to both RCD’s (left) or a flat surface (right).

Then, it is mandatory to perform several readings taken from different observation positions and merge them in a structure that allows the extraction of the desired information, i.e. the characterization of the object.

Figure 3: Two possible targets that produce the same return for a two sensor configuration

Figure 4: A set of cells with various levels of occupancy, distinguished by the grey levels

3.1 Representation

The chosen representation was to divide the workspace into cells. To each cell was assigned a value that represents the knowledge level about its occupancy. Figure 4 shows a small grid with various levels assigned to the cells: white represents unoccupied, black occupied and grey unknown.

This value is updated each time the area it represents is scanned. Thus, after a few valid observations of the region represented by a given cell, it is possible to say if it is occupied or not.

4 IMPLEMENTATION

For implementation purposes the cell has been defined as a structure with two fields: the first is level that conforms to the above description except that its value range from 0 to 255, and the second is flag that can have three discrete values occupied, unoccupied and unscanned.

As the cell value ranges from 0 (empty) to 255 (occupied), this field is initialized with the value 128 that corresponds to a middle level, and the flag is initialized with "unscanned". If we consider the existence of an a priori map, the cells that correspond to the a priori known objects are initialized with the maximum
value and flag with "occupied".

A grid size of 10x10cm was chosen because it should allow the detection of small objects but should not be computationally heavy. As the standard deviation of range errors is smaller than the cell size, we did not consider the stochastic sensor model previously described. So, for a range value r, there is a set of cells that enclose all possible target locations that could produce this value. This set also contains the arc above referred as RCD (figure 5) and can be viewed as its discretization.

For short range values, the RCD is contained on a single cell, then it contains surely the point that produced the echo, and then it is assigned a probability of 100%. For larger range values the RCD spans over several cells, and then this certainty must be shared by all of them. So each one is updated by 1/n, where n is the number of cells that contain the RCD.

4.1 Updating the grid

Once a sensor measurement is obtained, several steps are needed; given the robot’s position and orientation at the point where the measurement was taken, the determination of the sensor world coordinates is obtained by:

\[ X^* = TRX \]  (3)

where \( X^* \) is the vector of the sensor world coordinates, \( T \) the translation matrix, \( R \) the rotation matrix and \( X \) the sensor coordinates in the robot frame. If the sensor has an opening angle \( \theta \), the cells that are subject to change are those that fall inside the region limited by the two line segments and the arc as in Figure 6.

Considering a coordinate system centered in the sensor with the X axis along the scanning direction, and given the scan value \( R \), the arc and the line segments are easily determined. Then by using a coordinate transformation as in 3 their world coordinates are obtained. Given the frontier points a filling method is used to find the cells swept by the sonar.

4.2 Cells’ occupied / unoccupied transition

The cells’ flag transition between occupancy states is done with hysteresis and is related with the cells level in the following way: If a cell or a group of cells, previously marked as empty, reaches a threshold level \( T_e \), they are considered as being occupied. And the inverse happens with groups of cells that were previously marked as occupied and fall below the \( T_e \) level. By using the threshold affected by hysteresis the changes of state due to spurious reflections occur less frequently (Figure 7).

5 EXPERIMENTAL RESULTS

Figure 8 shows the levels that the cells reached after performing some scans while moving the platform. This movement was made in part of a room containing several objects (chairs, desks, boxes, etc.). This figure has been marked with the position of a wall (w1) and a column (c). Figure 9 shows the the cells states that correspond to the application of thresholding with hysteresis to theirs levels.
6 FINAL REMARK

This algorithm copes with changes in the environment, for example: a group of cells that were previously occupied by a chair that has been moved will be marked as empty and those that correspond to the new chair position will be marked as occupied. This feature allows the operation of a mobile robot, in an environment subject to changes.

REFERENCES


