Mobile Robots Navigation, Mapping, and Localization Part II

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INTRODUCTION

In addition to the capability to navigate from a point of origin to a given goal and avoiding all static and dynamic obstacles, a mobile robot must posses another two competencies: *map building* and *localization* in order to be useful.

A mobile robot acquires information of its environment via the process of map building. Map building for mobile robots are commonly divided into *occupancy grid* and *topological* maps. *Occupancy-grid* maps seek to represent the geometric properties of the environment. *Occupancy-grid* mapping was first suggested by Elfes in 1987 and the idea was published in his Ph.D. thesis (A. Elfes, 1989) in 1989. *Topological* mapping was first introduced in 1985 as an alternative to the *occupancy-grid* mapping by R. Chatila and J.-P. Laumond (R. Chatila, & J.-P. Laumond, 1985). *Topological* maps describe the connectivity of different locations in the environment.

The pose of a mobile robot must be known at all times for it to navigation and build a map accurately. This is the problem of localization and it was first described in the late 1980's by R. Smith et al (R. Smith et al, 1980). Some key algorithms for map building and localization will be discussed in this article.

BACKGROUND

Map building is the process of acquiring information of the environment via sensory data and representing the acquired information in a format that is comprehensible to the robot. The acquired map of the environment can be used by the robot to improve its performance in navigation.

Localization is the process of finding the pose of the robot in the environment. It is perhaps the most important competency that a mobile robot must possess. This is because the robot must know its pose in the environment before it can plan its path to the goal or follow a planned path towards the goal.

In this article, two key algorithms for map building: *occupancy-grid* and *topological* mapping are discussed. The *occupancy grid* and *topological* maps are two different methodologies to represent the environment in a robot's memory. Two key localization methods: Localization with *Kalman filter* and *particle filter* are also reviewed.

MAP BUILDING

As seen from the *integrated algorithm* from part I of the article, a mobile robot must be able to acquire maps of an unknown environment to achieve higher level of autonomy. Map building is the process where sensory information of the surrounding is made comprehensive to a mobile robot. In this section, two key approaches for map building: *occupancy-grid* and *topological* mapping are discussed.

Occupancy-Grid Maps

Occupancy-grid maps (H.P. Moravec, 1988; H.P. Moravec et al, 1989; A. Elfes, 1987, A. Elfes, 1989; S. Thrun et al, 2005) represent the environment as a tessellation of grid cells. Each of the grid cells corresponds to an area in the physical environment and holds an occupancy value which indicates the probability of whether the cell is occupied or free. The occupancy value of the i^{th} grid cell at current time t will be denoted by $p_{t,i}$. Note that $p_{t,i}$ must be within the range of 0 to 1 following the axioms of probability. $p_{t,i}$ = [0,0.5) indicates the confidence level of a cell being empty where 0 indicates absolute certainty that the cell is empty. $p_{t,i}$

= (0.5,1] indicates the confidence level of a cell being occupied where 1 indicates absolute certainty that the cell is occupied. $p_{t,i}$ = 0.5 indicates that the cell is an unexplored area.

A robot does not have any knowledge of the world when it was first placed in an unknown environment. It is therefore intuitive to set $p_{t,i} = 0.5$ for all i at time t = 0. The map is updated via the *log odds* (S. Thrun et al, 2005) representation of occupancy. The advantage of *log odds* representation is that it can avoid numerical instabilities for probability near 0 or 1. The i^{th} grid cell that intercepts the sensor line of sight is updated according to

$$l_{t,i} = l_{t-1,i} + l_{sensor} \tag{1}$$

where $l_{t-1,i}$ is the *log odds* computed from the occupancy value of the cell at *t-1*.

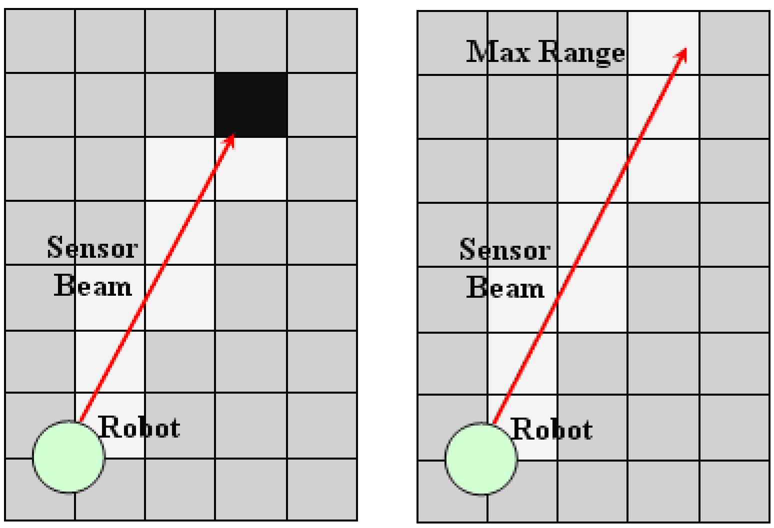
$$l_{t-1,i} = \log \frac{p_{t-1,i}}{1 - p_{t-1,i}} \tag{2}$$

$l_{sensor} = l_{occ}$ if the cell corresponds to the sensor measurement and $l_{sensor} = l_{free}$ if the range to the cell is shorter than the sensor measurement. The other cells in the map remain unchanged.

Figure 1(a) illustrates the update process for the map. The cell that corresponds to the sensor measurement is shaded black and all the cells that intercept the sensor measurement beam are shaded white. Figure 1(b) shows a case where the sensor measurement equals to maximum sensor range and $l_{sensor} = l_{free}$ for all cells that intercepts the sensor beam. This is because it is assumed that no obstacle is detected if the sensor measurement equals to maximum sensor range. l_{occ} and l_{free} are computed from

$$l_{occ} = \log \frac{p_{occ}}{1 - p_{occ}} \text{ and } l_{free} = \log \frac{p_{free}}{1 - p_{free}} \tag{3}$$

where p_{occ} and p_{free} denote the probabilities of the sensor measurement correctly deducing whether a grid cell is occupied or empty. The two probabilities must add up to 1 and their values depend on the accuracy of the sensor. p_{occ} and p_{free} will have values closer to 1 and 0 for an accurate sensor. The values of p_{occ} and p_{free} have to be determined experimentally and remain constant in the map building process.



(a) *(b)*

Figure 1. Updating an occupancy grid map (a) when an obstacle is detected (b) when a maximum range measurement is detected, i.e. it is assumed that in this case no obstacle is detected

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