17th International Conference
ENGINEERING MECHANICS 2011
Svratka, Czech Republic, 9 – 12 May 2011

CONCURRENT MAPPING AND LOCALIZATION BASED ON POTENTIAL FIELDS

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Abstract: *Presented paper deals with Concurrent Mapping and Localization as a method to build the local map for the autonomous mobile robot. Building accurate local map is necessary for the successful navigation through the crowded environment densely populated with dynamic obstacles. The occupancy grid mapping algorithm was used due to the high uncertainty in the measurements of dynamic obstacles. As the occupancy grid algorithm is of probabilistic nature the implementation is straightforward and is also capable to generate the results in real-time.*

Keywords: ***Occupancy grid mapping, binary Bayes filter.***

1. Introduction

Concurrent Mapping and Localization (CML), also known as Simultaneous Localization and Mapping (SLAM) problem belongs to the most complicated tasks in mobile robotics. In some simple cases the autonomous robot could solve only the mapping or localization problem separately. The mapping problem is addressed to the robots for which the location is known and the robots goal is to create a map of its environment (Thrun et al., 2005). On the other hand, the localization problem is usually solved via robot with known map and its goal is to find the path through environment (Lazanas & Latombe, 1995).

When the map and initial position of the robot are unknown, the online CML problem needs to be solved to accomplish the navigation task. The robot has to create online map from sensor readings and simultaneously localize itself in such a map (Deans, 2005).

Presented paper briefly describes CML algorithm based on occupancy grid method, which belongs to the group of probabilistic mapping techniques. The method is used to create a real-time local map of nearby environment of autonomous mobile robot during its movement in crowded space full of dynamic obstacles - moving people. Online generated local map is used to navigate the robot through the environment.

The paper is organized as follows: Chapter 2 describes binary Bayes filter with static state which is the basic principle in Occupancy grid mapping method. The Occupancy grid mapping method is described in chapter 3 and the final results obtained from experiments on mobile robot Advee are shown in chapter 5.

2. Binary Bayes filter with static state

Binary Bayes filter with static state is a special case of discrete Bayes filter (Thrun et al., 2005) and is usually presented in log odds form. The static state means that the state does not change in time (in other words: during sensing). In practice, this is the case when the robot is faced to detect some gap in its path. So the robot has to decide based on repetitive sensor readings if the gap is presented or not (binary static state – the presence of the gap does not depends on time).

The algorithm of binary Bayes filter with static state is shown in Tab. 1.

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Tab. 1: Binary Bayes filter algorithm.

Step	Description
1.	***BinaryBayesFilter(*** l_{t-1} ***,*** x , z_t ***)***
2.	***return*** $l_t = l_{t-1} + \log \frac{p(x \mid z_t)}{1 - p(x \mid z_t)} - \log \frac{p(x)}{1 - p(x)}$

where:

- l_t is a posterior belief over a binary state
- x is a static state; it does not change in time
- z_t is an actual measurement
- $p(x \mid z_t)$ is an inverse measurement model; It is a distribution over the binary state variable x as a function of measurement z_t
- $p(x)$ is the prior probability of the state x

The part of the equation $\log \frac{p(x)}{1 - p(x)}$ can be written in short form as $l(x)$. Usually it is a constant variable l_0 as it represents the prior information about the process.

3. Occupancy grid mapping

Occupancy grid mapping technique is a probabilistic method based on binary Bayes filter with static state. The map of environment is represented as a discrete grid $m = \{m_i\}$

Each cell m_i in the grid represents the binary state occupied/free, practically there is occupancy information only (0-free; 1-occupied).

The algorithm of occupancy grid mapping is a version of binary Bayes filter as it is shown in Tab. 2. The inverse sensor model on step 3 represents the probability that the given cell in the map x is occupied when sensor performs the measurement z_t . The algorithm of inverse sensor model is shown in Tab. 3.

Tab. 2: Occupancy grid algorithm.

Step	Description
1.	***OccupancyGridMapping(*** $\{l_{t-1,i}\}$ ***,*** x , z_t ***)***
2.	***for*** m_i ***in*** m
3.	$l_{t,i} = l_{t-1,i} + InverseSensorModel(m_i, x_t, z_t) - l_0$
4.	***return*** $\{l_{t,i}\}$

4. Inverse sensor model

The inverse sensor model represents the probability $p(m_i \mid x_t, z_t)$ in log odds form. A few cases are shown on figure 1. There are results from sensor model based on different sensor readings.

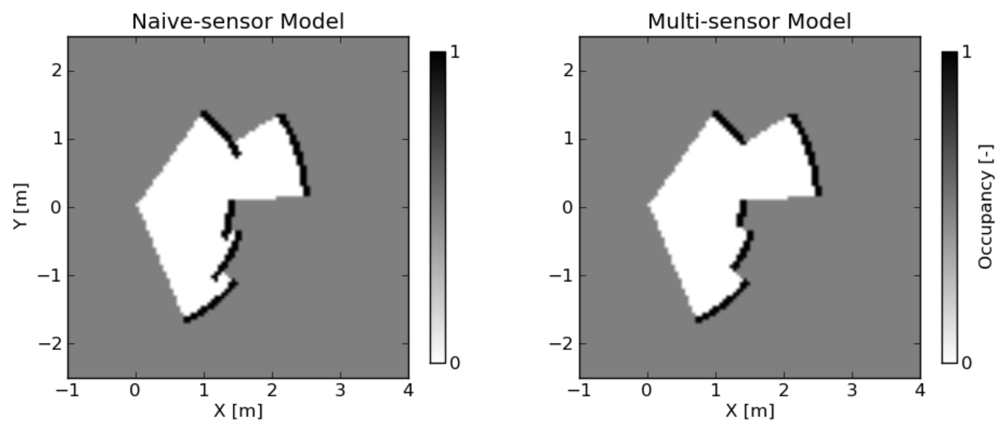

Fig. 1: Inverse sensor models.

This sensor model can be implemented in various ways. The simplest implementation is shown on figure 1-left which describes so called single sensor model. This sensor model considers each sensor beam independent on each other (naive sensor model). This consideration can be an issue if the robot deals with some kind of range finders (ultrasonic or laser) that returns an array of range measurements for a set of angles. There are some errors on borders of sensor beams.

This problem can be solved with multi-sensor model. This kind of model includes the cross-correlation of nearest sensor beams. This approach returns more realistic results (see Fig. 1 - right).

Tab. 3: Inverse sensor model algorithm.

Step	***Description***
1.	***InverseSensorModel(*** m_i, x_t, z_t ***)***
2.	$r_z, \varphi_z = f(x_t, z_t);\ r_m, \varphi_m = f(x_t, m_i)$
3.	***if*** $\varphi_m < \varphi_z + \beta$ *and* $\varphi_m > \varphi_z - \beta$
4.	***if*** $r_m < r_z + 1$ *and* $r_m > r_z - 1$ ***return*** $l_{occupied}$
5.	***elif*** $r_m \le r_z - 1$ ***return*** l_{free}
6.	***else return*** l_0

Where r_z, φ_z are radius and angle of sensor beam end point, r_m, φ_m are radius and angle of given cell in the map, both relative to the actual position of the robot x_t, β is the width of sensor beam, the log odds values describes the walls or free space as follows: $l_{occupied} = 1$, $l_{free} = 0$, $l_0 = 0.5$.

5. Building a local map

Practical experiments were performed on autonomous mobile robot Advee. Advee is equipped with sixteen ultrasonic sensors SRFS08, that are used for collision detection and obstacle avoidance. Sensors are located around the robot in the planar configuration, therefore the task in hand can be considered 2D. Each ultrasonic sensor is capable to detect an obstacle up to 3 meters and the sonic beam is 50 degrees wide. The usage of this kind of sensors is motivated with the nature of obstacles (usually the moving people).

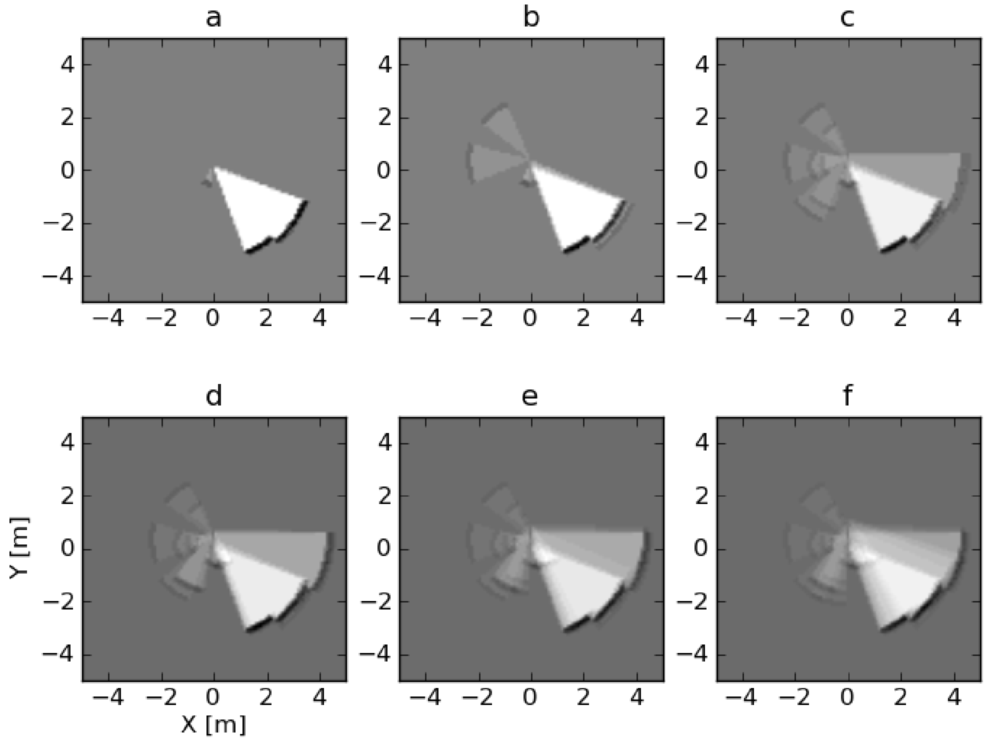

Fig. 2: Building a local map from sensor scans.

The local map generated via occupancy grid method uses several complete sensor scans. An example is shown in Fig. 2. On that figure one can observe subsequent building of the local map from the sensor readings. The process begins in Fig. 2a and ends in Fig. 2f. In each figure the local map is updated based on the sensor readings. In Fig. 2a only two readings are registered (other readings are invalid or obstacle undetected), in Fig. 2b there are four readings, etc. Resulting local map is used for local path planning and obstacle avoidance.

6. Conclusions

We have presented a method called occupancy grid mapping as an approach to build a local map for navigation of an autonomous robot through unknown environment. Presented method was integrated into the navigation system of autonomous mobile robot Advee that has to move in crowded environment densely occupied with dynamic obstacles. The tests in real world environment proved that the method can successfully build local map of the close surrounding of the robot. Such information is further utilized in the motion planner of the robot.

Acknowledgement

Published results were acquired with the support of the Academy of Sciences of the Czech Republic under the research plan AV0Z20760514 "Complex dynamical systems in thermodynamics, fluid and solid mechanics" and with the support of the Operational Programme Education for Competitiveness, project number CZ.1.07/2.3.00/09.0162 „Knowledge and Skills in Mechatronics – Innovations Transfer to Practice“.

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