

FAST SOLUTION OF THE MOBILE ROBOT LOCALIZATION PROBLEM

S. Věchet¹, J. Krejsa²

Summary: *The localization and path planning problem belong to basic tasks in navigation of mobile robots. Markov localization seems to be a good way to successful localization. However it is difficult to use this method for real-time applications. To avoid this limitation we developed, implemented and tested a new algorithm of robot localization in real-time. In this paper we describe theoretical principles and practical results for the new localization algorithm.*

1. Introduction

Mobile robot localization is the problem of estimating a robot's pose (location, orientation) relative to its environment. The localization problem is a key problem in mobile robotics, it plays a main role in various mobile robot systems.

There are three different issues in robot localization:

1. The most simple localization problem is position tracking. Here the initial robot pose is known, and the problem is to compensate incremental errors in a robot's odometry.
2. More challenging is the global localization problem, where a robot doesn't know its initial pose but has to determine it from scratch instead. The global localization problem is more difficult, since the error in the robot's estimate cannot be assumed to be small.
3. Even more difficult is the kidnapped robot problem, in which a well-localized robot is teleported to some other place without being told. This problem differs from the global localization problem in that the robot might resolutely believe itself to be somewhere else at the time of the kidnapping. The kidnapped robot problem is often used to test a robot's ability to recover from catastrophic localization failures.

Finally, all these problems are particularly hard in dynamic environment, if robot operates in the proximity of moving objects which corrupt the robot's sensor measurements.

Many of existing algorithms address only the position tracking problem. The nature of small, incremental errors makes algorithms such as Kalman filters applicable. Kalman filters estimate posterior distributions of robot poses conditioned on sensor data. This limitation is overcome by two related families of algorithms: localization with multi-hypothesis Kalman filters and Markov localization.

1 Ing. Stanislav Věchet, PhD. Institute of Automation and Computer Science, Brno University of Technology, Technická 2, 616 69, Brno, Czech Republic, tel: +420 541 143 356, email: vechet.s@fme.vutbr.cz
2 Ing. Jiří Krejsa, PhD. Institute of Thermomechanics – Brno branch, Czech Academy of Sciences, Technická 2, 616 69, Brno, Czech Republic, tel: +420 541142885, email: jkrejsa@umt.fme.vutbr.cz

Multi-hypothesis Kalman filters in practical implementation extract low-dimensional features from the sensor data, thereby ignoring much of the information acquired by a robot's sensors. Markov localization (ML) algorithms represents beliefs by piecewise constant functions (histogram) over the space of all possible poses. Kalman filters offer an elegant and efficient algorithm for localization. However, the restrictive nature of the belief representation makes plain Kalman filters inapplicable to global localization problem. As the Markov localization seems to be a good way to robot localization, in our initial experiments we discovered that this method is problematic in real-time application due to its computational requirements. Standard estimating time for complex environment can extend to the magnitude of minutes.

2. Localization method

To meet the localization method requirements, new algorithm based on pre-computed world scan and comparison with actual neighborhood scan was developed, implemented and tested. The key idea is to estimate a probability density over the state space conditioned on the data. This is typically called the "belief" and is denoted as

$$Bel(x) = r(x, a, S) \quad (1)$$

where x is the state (robot pose), a denotes the actual perceptual data reading by robot in given state (such as infrared sensor measurements), S represents a set of m samples distributed uniformly in state space, r is a reward function which return the „belief“ for given inputs x, a, S .

The belief is computed for each sample as follows:

1. assume the robot's pose is x , and let o denote the individual sensor beam with bearing α relative to the robot then the distance d reading for this beam is given according to

$$d_j = g(x, o_j) \quad (2)$$

$g(x, o_j)$ denote the measurement of an ideal sensor

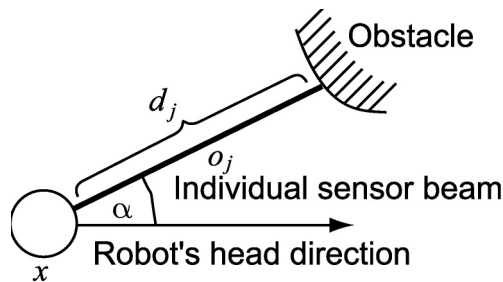


Fig. 1: Individual distance measurement

2. for n beams we have complete neighborhood scan

$$d = \{d_j\}_{j=1,\dots,n} \quad (3)$$

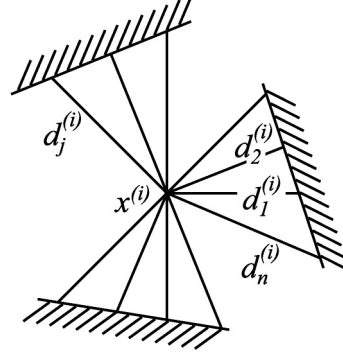


Fig. 2: Complete neighborhood scan

3. than the set S of m samples is

$$S = \{x^{(i)}, d^{(i)}\}_{i=1,\dots,m} \quad (4)$$

4. and the reward function r is

$$r(x^{(i)}, a, S) = \sum_{j=0}^n (d_j^{(i)} - a_i)^2 \quad (5)$$

3. Simulation experiments

For tests in real world and verification of theoretical and simulation results we built simple mobile test robot MLOK I, controlled from PC and equipped with proximity sensors (pair of GP2D12 infrared sensors with 100-800 mm range in full 360° scan range) and step motors giving the robot maximum speed of 100mm/sec. The minimal resolution of the step move in straight direction is limited to 1 cm and to 5° for the rotation.

Presented localization method was successfully tested on simulation tasks and also in real world. Simulation test was performed in virtual environment. This environment was represented by room with dimensions 6x8 meters. In this room was number of obstacles which represented standard room equipment.

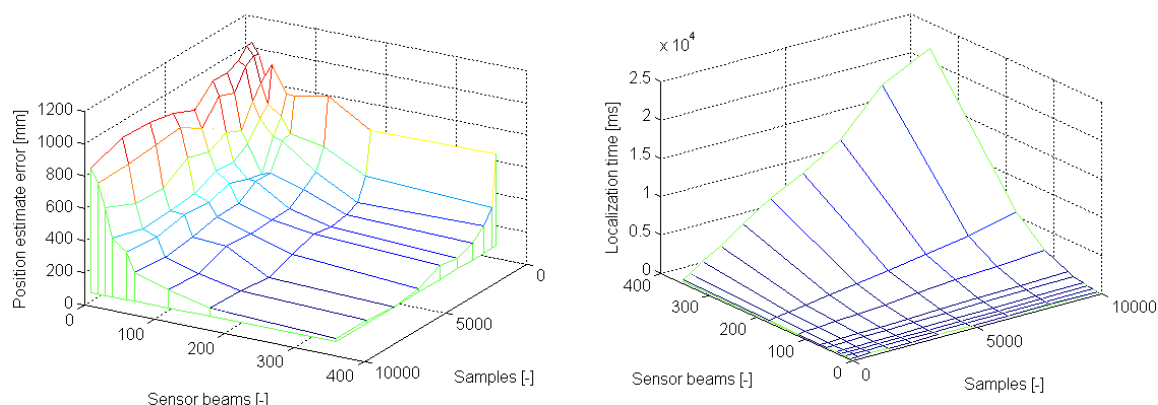


Fig. 3: Influence of number of sensor beams and number of samples to position estimate error(left) and to localization time(right).

The robot's task was to localize itself in the room. The influence of number of localization parameters (e.g. the number of sensor beams used for robot's neighborhood scan, sensor reading error, number of samples, ...) to localization time and position estimate error was tested. This results you can see on figure 3.



Fig. 4: Localization in simulation experiments. Room dimensions: 6x8m, 1600 samples, 72 beams, localization time 120ms, noise 20%

Typical results of localization task are shown on the Figure 4 and 5. The gray scale rectangles represent the belief that the robot is on given pose. Based on these results the experiments in real world were prepared. Localization method was successful, but the limitations of small sensor range little distorted the results in comparison with simulation. Better scene sensors are necessary for more complex verification of this localization method. Further details were published in [2].

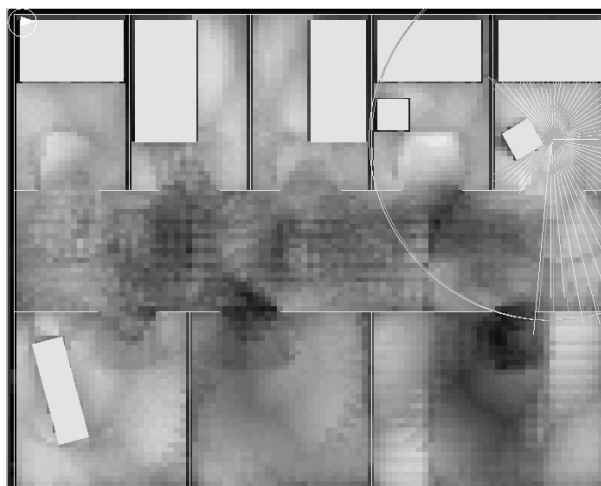


Fig. 5: Localization in simulation experiments. Room dimensions: 6x8m, 10000 samples, 72 beams, localization time 5s, noise 20%

4. Conclusions

In present time a final localization experiments on simple mobile robot MLOK II are performed. This robot is equipped with infrared sensors of higher measurement range compared to MLOK I (about 1.5m). These experiments form a basement for more sophisticated navigation method which belongs to the SLAM (Simultaneous Localization And Mapping) problems, capable of localization with initially unknown map, when robot's goal is to create consistent map and find itself on the real position.

5. Acknowledgement

This work was supported by Czech Ministry of Education under project MSM 0021630518 "Simulation modelling of mechatronic systems".

6. References

- [1] Krejsa Jiří, Věchet Stanislav: Markov Localization for Mobile Robots: Simulation and Experiments, *Engineering Mechanics 2005*, 2005
- [2] Věchet Stanislav, Krejsa Jiří: Real Time Localization for Mobile Robot, *Engineering Mechanics journal*, Volume 12, Number A1, pp. 3-10, 2005