

Observation model for Monte Carlo Localization

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Abstract: Accurate and robust mobile robot localization is very important in many robot applications. Monte Carlo localization (MCL) is one of the robust probabilistic solutions to robot localization problems. The sensor model used in MCL directly influence the accuracy and robustness of the pose estimation process. The classical beam model suffers from non-smooth likelihood functions. The non-smooth likelihood function has two negative effects on the localization process. The first one when the likelihood function has extreme peaks because of low measurement noise. It has been shown that the MCL would fail in such conditions. The second one when the robot operates in highly cluttered environments, small changes in the pose of the robot can lead to large changes in the measured values that result in localization degradation. A common solution is to artificially smooth the likelihood function or to use a small fraction of the measurements. In this research, an adaptive sub-sampling of the measurements is proposed to improve the likelihood function. The sampling is based on the complete scan analysis. The specified measurement is accepted or not based on the relative distance to other points in the 2D point cloud. Real data recorded from Sick LMS 200 laser scanner mounted over pioneer 3at robot has been used to prove the smoothness of the resultant likelihood compared to the original one.

This is an ongoing research!

Keywords: Localization, robotics, Particle filter, Monte Carlo localization, sensor model.

1. INTRODUCTION

Probabilistic localization techniques have been demonstrated to be a robust approach to mobile robot localization. They allow the vehicles to globally localize themselves, to efficiently keep track of their position, and to even recover from localization failures. One of the key challenges in context of probabilistic localization, however, lies in the design of the so-called observation model $P(\mathbf{z}|x, m)$ which is a likelihood function that specifies how to compute the likelihood of an observation \mathbf{z} given the robot is at pose x in a given map m . For probabilistic approaches the proper design of the likelihood function is essential (Pfaff et al. (2008)).

Several sensor models are based on the basic concept of the well known beam model that is also used in traditional MCL methods. The beam model considers the sensor readings as independent measurement vector \mathbf{z}

$$\mathbf{z} = [z_1, z_2, \dots, z_K] \quad (1)$$

which is represented by a one dimensional parametric distribution function depending on the expected distance in the respective beam direction.

The model calculates the likelihood of each individual beam to represent its one-dimensional distribution by a parametric function depending on the expected range measurement.

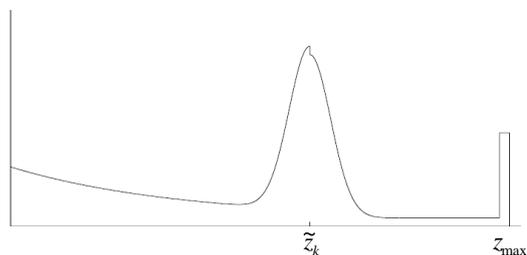


Fig. 1. Single beam distribution

This model is sometimes called raytracing or ray cast model because it relies on ray casting operations within an environmental model e.g., an occupancy grid map, to calculate the expected beam lengths.

$$P(\mathbf{z}|x, m) = \prod_{k=1}^K P(z_k|x, m) \quad (2)$$

This likelihood function can have a major influence on the performance of Monte Carlo Localization. (Thrun et al. (2001)) observed that more particles are required if the likelihood function is peaked. To deal with this several techniques have been proposed. Either to directly sample from the observation model which is inaccurate (Thrun et al. (2001); Lenser and Veloso (2000)) or dynamically adapt the number of particles as in KLD sampling, (Fox (2003)). However, for very accurate sensors, the number of particles could be very large. An other solution is to inflate the measurement uncertainty or neglect some of the sensor beams. In this research, an adaptive sub-sampling of the measurements is proposed to improve the likelihood function. The sampling is based on the complete scan analysis. It is adaptive, because the sampling may differ from scan to another. The specified measurement is accepted or not based on the relative distance to other points in the 2D point cloud. Instead of using all the 'K' beams in the equation above, adaptively reduce the number of beams in each scan according to the complete scan analysis (euclidean distance in this case)

$$P(\mathbf{z}|x, m) = \prod_{k=1}^K \bar{P}(z_k|x, m) \quad (3)$$

$$\bar{P}(z_k|x, m) = \begin{cases} 1 & \text{if } |z_k - z_{k-1}| \leq \delta \\ P(z_k|x, m) & \text{if } |z_k - z_{k-1}| > \delta \end{cases}$$

The δ is the distance threshold value. Based on the assumption that the very close points in the 2D space are most likely to be reflected from the same obstacle and therefore can be reduced. On the other hand, measurements that well separated in the 2D space are most likely to be reflected from different obstacles.

2. RESULTS

The above described reduction scheme has been tested on real data taken from LMS200 Laser scanner mounted on Pioneer 3at mobile robot Fig. 2.



Fig. 2. LMS200 Laser scanner mounted on Pioneer 3at mobile robot used for the data recording.

Fig.3 shows the likelihood relative function peaks for both classical beam model (in blue) and the reduced one (in red). The y-axis is the ratio between the first and the peaks in the likelihood function. It is clear that the peaks have been reduced greatly. The x-axis represents about 1600 scan recorded during robot mapping of the lab.

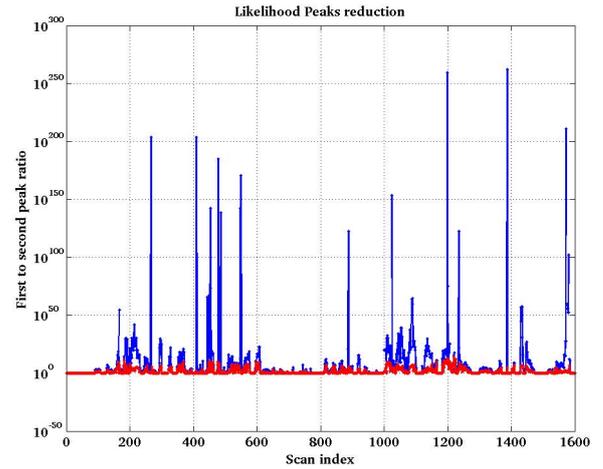


Fig. 3. Likelihood peaks reduction

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