VIRTUAL MOBILE ROBOT LOCALIZATION

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ABSTRACT

This paper deals with the fundamental problem in mobile robotics. Accurate knowledge about self-position relative to the environment is in many cases essential for the robot to be able to plan future actions. The information used by the robot to obtain knowledge about its position is always to some extent inaccurate and thereby the localization problem is transformed into estimation of probability density function of current robot state. In this paper, the use of CONDENSATION algorithm for robot localization in known environment is discussed and a framework for simulation of mobile robot, which can be used for experiments and classroom demonstrations, is presented.

1. INTRODUCTION

To know a self-position relative to the surrounding environment is one of the essential requirements for autonomous operation of mobile robots. There can be two points of view on this problem. Either the environment is unknown and robot uses sensors to obtain knowledge about the objects currently surrounding it or the environment is known to the robot and it estimates its position by matching current sensor information with the environment model. Some knowledge about possible movement of the robot between two time points is always available. This knowledge can be used in known environments for position tracking [1] and in unknown environments, to simultaneously track the position of a robot and build environment model [2]. Simultaneous localization and mapping (SLAM) is very complex task especially in dynamic and unmodified environments. In the rest of this paper, only localization and position tracking in known environment will be considered.

The localization problem is formalized in section 2. and its solution using CONDENSATION algorithm is presented in section 3. An implemented framework for mobile robot simulation and localization is presented in section 4. Finally, results are summarized and future work is outlined in section 5.

2. ROBOT LOCALIZATION

The goal of robot localization is to estimate robot state x_k (usually 3 dimensional - position and orientation) at discrete time-steps k based on acquired measurements from the sensors $Z^k = z_i, i = ..k$ and knowledge about possible movement of the robot. This is essentiallv an instance of the Bayesian filtering problem where the estimated posterior density $p(x_k|Z^k)$ represents all the available knowledge about the current state x_k.

When assuming that the robot dynamics forms a temporal Markov chain – the current state x_k is only conditioned by previous state x_{k-1} and a known control input u_{k-1} – the robot motion model can be specified as $p(x_k|x_{k-1},u_{k-1})$. This allows us to describe the effect of robot motion (prediction phase) by

$$p(x_k|Z^{k-1}) = \int p(x_k|x_{k-1},u_{k-1})\, p(x_{k-1}|Z^{k-1})\, dx_{k-1}\,. \tag{1}$$

The next is the so called update phase. Assuming measurement z_k is independent on earlier measurements Z^{k-1}, the measurement model is used to incorporate measurement information and obtain the posterior density $p(x_k|Z^k)$ (see eq. 2). The measurement model $p(z_k|x_k)$ expresses the likelihood of the acquired observation z_k being generated by the robot in state x_k.

$$p(x_k|Z^k) \propto p(z_k|x_k)\, p(x_k|Z^{k-1})\,. \tag{2}$$

The prediction and update phases are repeated for all time steps. When the models are Gaussian distributions, this process can be solved using Kalman filter. Since this is not always sufficient, methods based on discretization of the state space were proposed (e.g. grid based Markov localization). These methods have also some limitations (e.g. computational and memory overhead) [1]. Finally, particle filters are considered the best choice for this purpose [2] for their precision, generality and computational effectiveness.

3. LOCALIZATION WITH CONDENSATION

CONDENSATION algorithm [3] belongs to family of methods called particle filters. It allows arbitrary probability densities as those are represented by set of N random samples (particles) $S_k = \{s_k^i | i = 1..N\}$. The local particle density directly represents the local value of corresponding probability density function. When applied to the localization problem [1] from section 2, the algorithm proceeds in this way:

Let S_{k-1} represents $p(x_{k-1}|Z^{k-1})$. In the prediction phase, the motion model is applied (see eq. 1) to each of the particles from S_{k-1} by sampling from $p(x_k|x_{k-1},u_{k-1})$. In this way, new set of particles S'_{k-1} representing $p(x_k|Z^{k-1})$ is created.

In the update phase (see eq.2), each of the samples from S'_{k-1} is assigned a weight according to the measurement model $p(z_k|x_k)$. S_k approximating $p(x_k|Z^k)$ is then obtained by sampling from S'_{k-1} where particles are selected with probability equal to their weight.

Although, the CONDENSATION algorithm could be very computationally demanding, in most cases the number of particles can be kept sufficiently low to ensure real-time operation. Another appealing property of the algorithm is its simplicity which is related to the easy integration of dynamic and meassurament models.

4. SIMULATION FRAMEWORK

As part of this work, a framework for mobile robot simulation has been implemented to serve as a simple experimental platform and to demonstrate the basic concepts of robot localization and of the CONDENSATION algorithm. The simulated environment is a grid-based world of arbitrary size and shape. The simulated robot imitates a car-like vehicle with two degrees of freedom and is currently equipped with two simulated sensors – compass and ranging sensor measuring distance to a wall in front of the robot. Both movement and measurements are effected by synthetic errors imitating errors in real environment. The extent of all errors can be arbitrary adjusted and individual sensors can be turned off. OpenGL was used to visualize the simulation and the estimated robot position distribution.

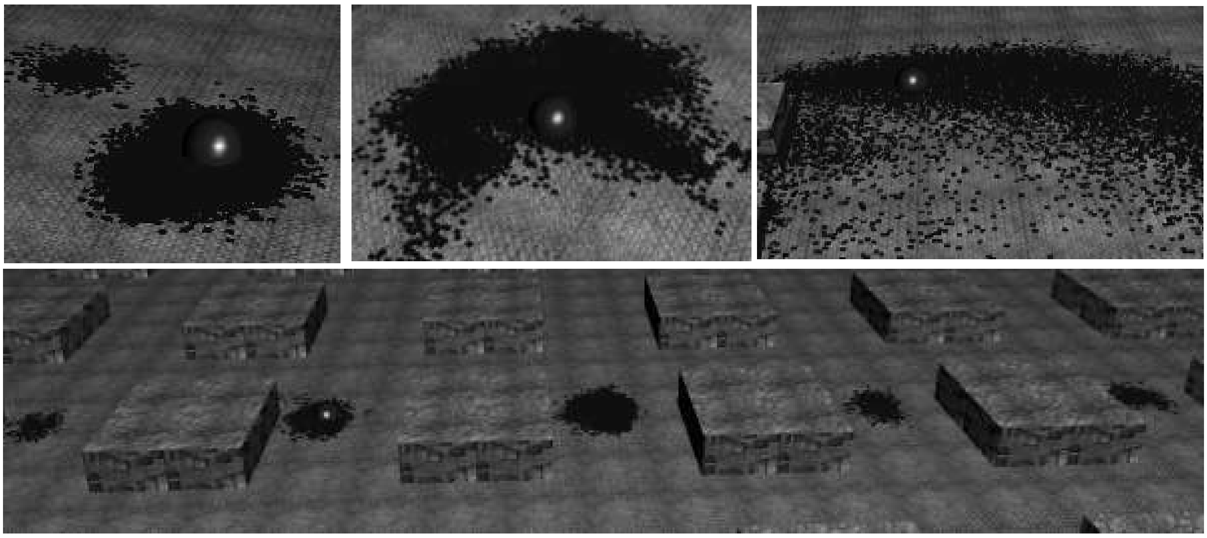

Figure 1: Visual output of the simulation – the gray spheres represent the robot true position – the estimated position PDF is black. The top row shows results of tracking during autonomous navigation using (from left) both meassurements, only distance meassurement and no messurement. The bottom row shows result of localization in highly self-similar environment – the result is a multimodal PDF because no information can be obtained from the current robot position to differentiate between the estimated positions.

5. CONCLUSION AND FUTURE WORK

CONDENSATION algorithm has proved to be very effective for mobile robot localization. It can localize the simulated robot in real-time in large and highly ambiguous environments using even information poor and very inaccurate measurements. Work in the near future will focus on implementation of navigation based on the current localization results. Further plans include implementation of SLAM based on the CONDENSATION algorithm and experiments with camera localization using distinctive image features.

REFERENCES/LITERATURA

[1] Dellaert, F., Burgard, W., Fox, D., Thrun, S., "Using the CONDENSATION algorithm for robust, vision-based mobile robot localization", IEEE Computer Society Conf. on Computer Vision and Pattern Recognition 1999.

[2] S. Se, D. Lowe, and J. Little, "Mobile robot localization and mapping with uncertainty using scale-invariant visual landmarks", The International Journal of Robotics Research, vol. 21, no. 8, pp. 735--758, 2002.

[3] M. Isard and A. Blake, "Condensation -- conditional density propagation for visual tracking", International Journal of Computer Vision 29(1), pp. 5--28, 1998.