Bayesian Filtering

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Introduction

A fundamental requirement for any robotics sytem is the ability to percieve and interact with its physical environment. Any reasonable interaction of a robot with its environment requires an internal model of its surroundings for purposes such as robot localisation, map generation, planning and to enable any other sensor processing to be placed in a spatial context. The data incorporated into such a model from sources such as odometry and sensors is noisy and may suffer from systemeatic error; this is compounded in realistic applications by the need for algorithmic approximations, producing an imperfect abstraction of the robot's environment described by a probability distribution.

At time t, the robot's state is represented by the variable x_t, the odometry data by u_t and sensor data by z_t. Naïvely, x_t may be expressed conditionally as a function of all previous states, sensor and odometry data: $P(x_t|x_{0:t-1}, u_{0:t}, z_{0:t})$. The tractability of this may be improved by ensuring or assuming that x is 'complete', that it satisifes the Markov Condition requiring x_t to be conditionally independent of $u_{0:t-1}$ and $z_{0:t-1}$ given the immediately preceding state x_{t-1}. Equivalently, this may be expressed as x_t containing all preceding information contributing to the conditional probabilty of future states.

As a matter of convenience, it is assumed that events occur in the following order:

1. A movmement u_t is executed
2. An updated prediction $\overline{bel}(x_t)$ of the state x is formed based on the movement instruction
3. A measurement z_t is taken
4. The measurement information is used to create a posterior belief $bel(x_t)$ from the prediction $\overline{bel}(x_t)$

Bayes' Filter

Kalman Filter

Particle Filter

Discussion