Particle filter for mobile robot tracking and localisation

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Overview

Goal

Introduction

Particle filter

Simulations

Goal

- To make a tutorial about a particle filter for AI
  - Comparable with the kalman filter tutorial
  - This tutorial shows the possible application of a Monte Carlo Simulation method (particle filter) for mobile robot tracking and localisation
  - Basic particle filter

Overview

Goal

Introduction

- General
- The Bayesian approach

Particle filter

Simulations

General

- Problem: estimate the state of a system that changes over time using sequence of noisy measurements
- Two models required:
  - System model
  - Measurement model
- If the models are in probablistic form the Bayesian approach is ideally suited

The Bayesian approach

- Approach provides a rigorous general framework for dynamic state estimation problems
- Construct the construct the posterior probability density function (pdf) of the state based on all available information including measurements
- The "complete" solution to the estimation problem
- An optimal (with respect to any criterion) estimate of the state may be obtained from the pdf

Overview

Goal

Introduction

Particle filter

- General
- Model description
- Prediction
- Resampling
- Update
- Numerical aspects/algorithmic details
- Estimate

General

- Objective: 'track' a variable of interest
- Can typically non-Gaussian and multi-model pdf $\leftrightarrow$ Kalman filter
- Key idea: *represent the required pdf by a set of ramdom samples with associated weights and compute estimates based on these samples and weights*
- Basis:
  - construct a sample-based representation of the entire pdf
  - actions modifying the state of the variable of interest according to the models
  - observation is made $\Rightarrow$ information about the variables

General: Importance sampling

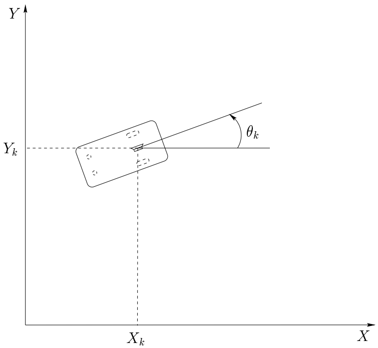
- Weigths of the samples are chosen using the principle of /emphimportance sampling
- $p(x) \propto \pi(x)$
  $x^i \sim q(x)$ with $q(x)$ the importance density
- Weighted approximation to $p(x)$:
  $p(x) \approx \sum_{i=1}^{N_s} w_k^i \delta(x_{0:k} - x_{0:k}^i)$ with $w^i \propto \frac{\pi(x^i)}{q(x^i)}$
- The Sequential Importance Sampling algorithm (SIS) supports recursive propagation of weights and support points

General: Importance sampling

- Here the importance sampling function is chosen equal to the prior calculated in the prediction step
- $\Rightarrow w_k^i = w_{k-1}^i * \underbrace{P(z_k|x_k)}_{\text{measurement model}}$

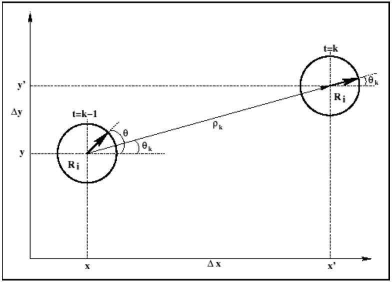
  $\Rightarrow$ Application of the proces model on the samples are samples of the proposal density
- Most obvious and most easy to understand choice.

Model description



- State: $\begin{pmatrix} x^k & y^k & \theta^k \end{pmatrix}^T$

Model description



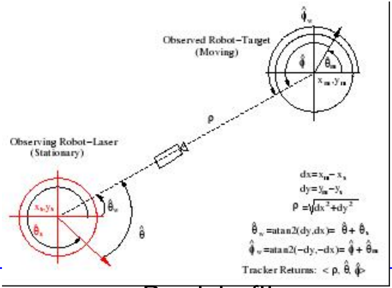
- Proces model
  - every motion modeled as first a rotation around axis followed by a translation

Model description

- Rotation: $\theta_{k+1} = \theta_k + \delta\theta + N(M_{rot}, \sigma_{rot})$ with $\delta\theta = atan\frac{\Delta y}{\Delta x}$
- Translation: Two sources of error: the actual traveled distance and the changes in orientation during the forward translation (=drift)
  $\theta_{k+1} = \theta_k + \delta\theta + N(M_{drft} * \delta\rho, \sigma_{drft} * \delta\rho)$
  $x_{k+1} =$
  $x_k + (\delta\rho + N(M_{trs} * \delta\rho, \sigma_{trs} * \delta\rho)) * cos(\theta_{k+1})$
  $y_{k+1} =$
  $y_k + (\delta\rho + N(M_{trs} * \delta\rho, \sigma_{trs} * \delta\rho)) * sin(\theta_{k+1})$
  $\theta_{k+1} = \theta_k + \delta\theta + N(M_{drft} * \delta\rho, \sigma_{drft} * \delta\rho)$

Model description

- Measurement model
  - US-sensor:
    $$z_k = \left(\frac{2a}{\sqrt{a^2+1}}\right) x_k + \left(\frac{-2}{\sqrt{a^2+1}}\right) y_k + \frac{2b}{\sqrt{a^2+1}} + \rho_m$$
  - RF-sensor:
    $$z_k = \begin{pmatrix} \rho \\ \theta \end{pmatrix} = \begin{pmatrix} \sqrt{(x_k - x_s)^2 + (y_k - y_s)^2} \\ atan\left(\frac{y_k - ys}{x_k - xs}\right) - \theta_k \end{pmatrix}$$



Prediction

- Uses the proces model (rotation and translation) to simulate the effect of hte action on the set of particles
- Add the apropriate noise to simulate the effect of noise on the variables of interest

Resampling

- To prevent the depletion of the population
- The effective sample size (ESS) indicates the effectiveness of the particles
- If $ESS < x.M$ with $M =$ number of particles $\Rightarrow$ Resample
- Resampling eliminates the particles with smaller weigths and duplicates the ones with higher weights in a probablistic way
- Three resampling algorithms
  - Select with replacement
  - Linear time resampling
  - Resampling by Liu et al.

Update

- Reevaluate the weight of the particles based on the latest sensory information available
- Thanks the the information obtained from the sensor the pdf can be described more accurately

Numerical aspects/algorithmic details

- Normalize the weights

Estimate

- Different options
  - The best particle:
    $\bar{x}_s = x_s^{max} \quad \text{with } x_s^{max} = x_i \quad \Big| \quad w_i = max\,(w_j)$
  - Weighted mean:
    $\bar{x}_s = \sum_{j=1}^{M} x_j w_j$
  - Robust mean:
    $\bar{x}_s = \sum_{j=1}^{K} x_j w_j \quad \Big| \quad \left| x_j - x_s^{max} \right| \leqslant \epsilon$

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Simulations

- Tracking
- Localisation

Tracking

- Prediction
  - Example 1
    - Initial: known pose
    - Uncertainty: traveled distance and angle during translation
    - Example 1
      Example 1 memory
  - Example 2
    - Initial: known pose
    - Uncertainty: angle during translation
    - Example 2
  - Example 3
    - Initial: known pose
    - Uncertainty: translation distance
    - Example 3

Tracking

- US measurement
  - Example 1
    - Initial: known pose
    - Uncertainty: traveled distance and angle during translation
    - Example 1
- RF measurement
  - Example 1
    - Initial: known pose
    - Uncertainty: traveled distance and angle during translation
    - Example 1

Tracking

- US and RF measurement
  - Example 1
    - Initial: known pose
    - Uncertainty: traveled distance and angle during translation
    - Example 1

Localisation

- US measurement
  - Example 1
    - Initial: unknown pose
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 1
- RF measurement
  - Example 1
    - Initial: unknown position, known orientation
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 1
  - Example 2
    - Initial: unknown pose
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 2

Localisation

- US and RF measurement
  - Example 1
    - Initial: unknown position, known orientation
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 1
  - Example 2
    - Initial: unknown pose
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 2
  - Example 3
    - Initial: unknown position, known orientation
    - Uncertainty: traveled distance, angle during translation, rotation angle
    - Example 3