B3M33MKR
Particle Filter

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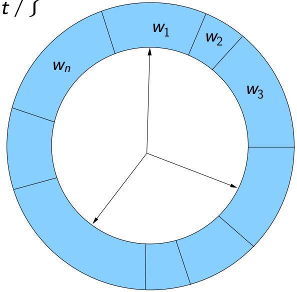
Assignment

- Implement Particle filter
  - Motion model
  - Sensor model
  - Integrate
- Input data are the same as for ICP
- Program template similar

Particle filter - the algorithm

Particle_filter(S_{t-1}, u_{t-1}, z_t)

$S_t = \emptyset$, $\eta = 0$
for $i = 1, \ldots, n$ **do** — Generate new particles
  Sample index j_i from the discrete distribution given by w_{t-1}
  Sample x_t^i z $p(x_t | x_{t-1}, u_{t-1})$ using $x_{t-1}^{j_i}$ and u_{t-1}
  $w_t^i = p(z_t | x_t^i)$ — Compute importance weight
  $\eta = \eta + w_t^i$ — Update normalization factor
  $S_t = S_t \cup \{\langle x_t^i, w_t^i \rangle\}$ — Insert a particle
end for
for $i = 1, \ldots, n$ **do** — Normalize weights
  $w_t^i = \frac{w_t^i}{\eta}$
end for



Odometry-based model for sampling

$u = \langle \delta_{rot_1}, \delta_{rot_2}, \delta_{trans} \rangle, x = \langle x, y, \phi \rangle => x' = \langle x', y', \phi' \rangle$

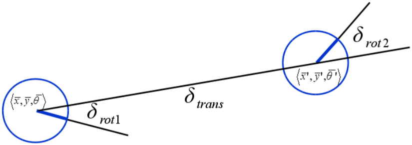
Random control

$$
\begin{aligned}
\hat{\delta}_{rot_1} &= \delta_{rot_1} + sample(\alpha_1|\delta_{rot_1}| + \alpha_2|\delta_{trans}|) \\
\hat{\delta}_{trans} &= \delta_{trans} + sample(\alpha_3|\delta_{trans}| + \alpha_4(|\delta_{rot_1}| + |\delta_{rot_2}|)) \\
\hat{\delta}_{rot_2} &= \delta_{rot_2} + sample(\alpha_1|\delta_{rot_2}| + \alpha_2|\delta_{trans}|)
\end{aligned}
$$

Position determination

$$
\begin{aligned}
x' &= x + \hat{\delta}_{trans} cos(\phi + \hat{\delta}_{rot_1}) \\
y' &= y + \hat{\delta}_{trans} sin(\phi + \hat{\delta}_{rot_1}) \\
\phi' &= \phi + \hat{\delta}_{rot_1} + \hat{\delta}_{rot_2}
\end{aligned}
$$

return $\langle x', y', \phi' \rangle$



Naive (not good!) approach

Correct approach

Points ..., α_2 is large

Correct approach

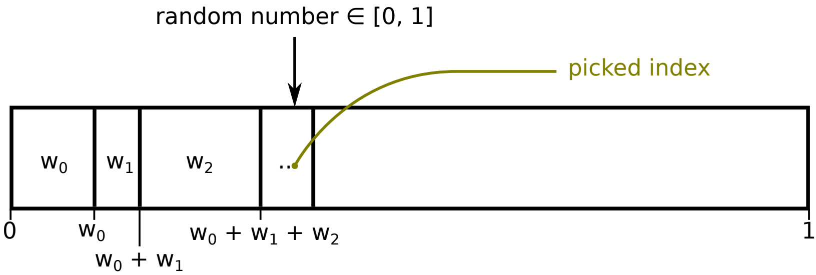
Points ..., α_3 is large

Correct approach

α_2 is large

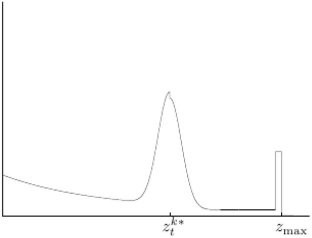
Correct approach

Roulette wheel



Sensor model

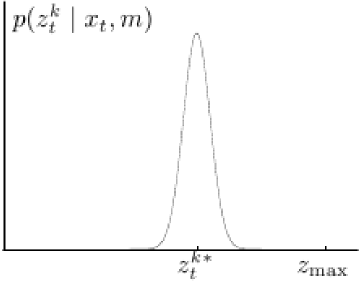
- The aim is to determine $p(z|m,x)$.
- Scan is composed from k measurements (beams): $z = \{z_1, z_2, \ldots, z_k\}$
- Individual measurements are independent given the robot position (strong assumption): $P(z|x,m) = \prod_{k=1} P(z_k|x,m)$



$$p(z|x,m) = \begin{pmatrix} \alpha_{hit} \\ \alpha_{short} \\ \alpha_{rand} \\ \alpha_{max} \end{pmatrix}^T \begin{pmatrix} p_{hit}(z|x,m) \\ p_{short}(z|x,m) \\ p_{rand}(z|x,m) \\ p_{max}(z|x,m) \end{pmatrix}$$

Beam-based model - components

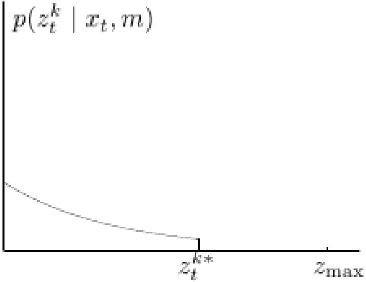
Measurement noise



$$p_{hit}(z|x,m) = \begin{cases} \eta N(z, z^*, \sigma_{hit}^2) & \text{if } 0 \leq z \leq z_{max} \\ 0 & \text{otherwise} \end{cases}$$

Normal distribution

Unexpected obstacles

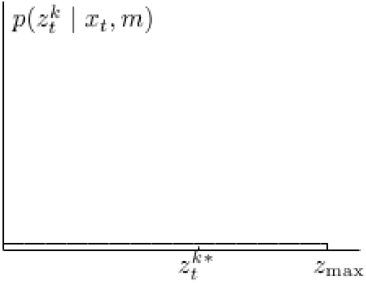


$$p_{short}(z|x,m) = \begin{cases} \eta \lambda_{short} e^{-\lambda_{short} z} & \text{if } 0 \leq z \leq z^* \\ 0 & \text{otherwise} \end{cases}$$

Exponential distribution

Beam-based model - components

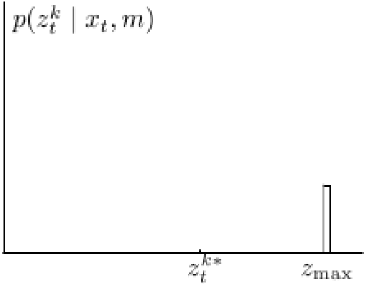
Random measurement



$$p_{rand}(z|x,m) = \begin{cases} \frac{1}{z_{max}} & \text{if } 0 \leq z \leq z_{max} \\ 0 & \text{otherwise} \end{cases}$$

Uniform distribution

Max range



$$p_{max}(z|x,m) = \begin{cases} 1 & \text{if } z = z_{max} \\ 0 & \text{otherwise} \end{cases}$$

Discrete distribution :-(