Improved Techniques for Grid Mapping with Rao-Blackwellized PFs

Grisetti et al.

Introduction

Murphy et al. introduced Rao-Blackwellized PFs for SLAM

The main problem of RBPFs

- # of particles to build an accurate map
- Particle Depletion

To fix those issues

To fix those issues

To increase the performance of RBPF:

- Proposal distribution considers accuracy of the sensors

  Less estimation error leads to less particles

- An adaptive resampling to prevent particle depletion

  Do the resampling whenever is needed

But what is RBPFs?

Rao-Blackwellized Particle Filters

To estimate $p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1})$ in which

- m is map
- $x_{1:t} = x_1 + x_2 + \ldots + x_t$ is robot's trajectory
- $z_{1:t} = z_1 + z_2 + \ldots + z_t$ is the observation
- $u_{1:t-1} = u_1 + u_2 + \ldots + u_{t-1}$ is the odometry measurement

Rao-Blackwellized Particle Filters(Cntd)

By using factorization:

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1}) = p(m \mid x_{1:t}, z_{1:t}).p(x_{1:t} \mid z_{1:t}, u_{1:t-1})$$

- The first part, $p(m \mid x_{1:t}, z_{1:t})$ is nothing but mapping with known poses
- The posterior $p(x_{1:t} \mid z_{1:t}, u_{1:t-1})$ is estimated by applying PF.

What kind of PF is that?

Sampling Importance Resampling(SIR)

Each particle has a potential trajectory of the robot.

As well as, an environment map of its own.

A RBSIR algorithm incrementally uses odom & sensor measurements for mapping.

How?

1- Sampling

Obtaining the next generation $\{x_t^{(i)}\}$ from $\{x_{t-1}^{(i)}\}$ by sampling form proposal distribution π

π is usually a probabilistic odometry motion model

2- Importance Weighting

Importance Sampling Principle:

$$w_t^{(i)} = p(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1}) \,/\, \pi(x_{1:t}^{(i)} \mid z_{1:t}, u_{1:t-1})$$

Proposal distribution π is in general not equal to target distribution

We can do it in a recursive way(by some assumption for efficiency)

$$w_t^{(i)} = w_{t-1}^{(i)} p(z_t \mid m_{t-1}^{(i)}, x_t^{(i)}).p(x_t^{(i)} \mid x_{t-1}^{(i)}, u_{t-1}) \,/\, \pi(x_t \mid x_{1:t-1}^{(i)}, z_{1:t}, u_{1:t-1})$$

3- Resampling

Proportional to importance weight

With replacement

4- Map Estimation

The map estimate for each particle

$$p(m^{(i)} \mid x_{1:t}^{(i)}, z_{1:t})$$

is computed based on its trajectory $x_{1:t}^{(i)}$ and the history of observations $z_{1:t}$

Improved Proposal Distribution

Local approximation of the posterior $p(x_t \mid m_{t-1}^{(i)}, x_{t-1}^{(i)}, z_t, u_{t-1})$ around the maximum likelihood function.

1. Using a scan-matcher to determine the meaningful area
2. K Sample in the meaningful area
3. Evaluated based on target distribution
4. $\mu_t^{(i)}$ & $\Sigma_t^{(i)}$ are determined for K sample points

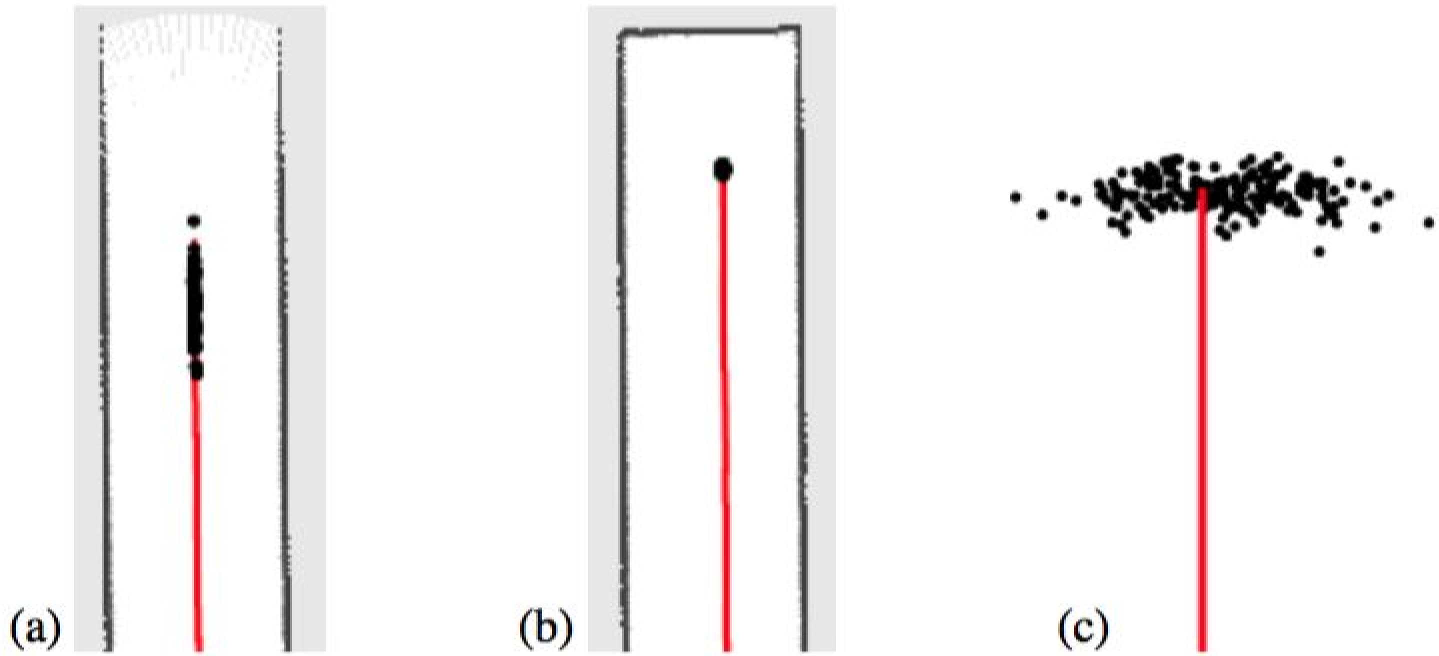
$$\mu_t^{(i)} = \frac{1}{\eta^{(i)}} \cdot \sum_{j=1}^{K} x_j \cdot p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_j \mid x_{t-1}^{(i)}, u_{t-1})$$

$$\Sigma_t^{(i)} = \frac{1}{\eta^{(i)}} \cdot \sum_{j=1}^{K} p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_j \mid x_{t-1}^{(i)}, u_{t-1}) \cdot (x_j - \mu_t^{(i)})(x_j - \mu_t^{(i)})^T$$

Improved Proposal

Using this proposal distribution weights can be computed as:

$$
\begin{aligned}
w_t^{(i)} &= w_{t-1}^{(i)} \cdot p(z_t \mid m_{t-1}^{(i)}, x_{t-1}^{(i)}, u_{t-1}) \\
&= w_{t-1}^{(i)} \cdot \int p(z_t \mid m_{t-1}^{(i)}, x') \cdot p(x' \mid x_{t-1}^{(i)}, u_{t-1})\, dx \\
&\simeq w_{t-1}^{(i)} \cdot \sum_{j=1}^{K} p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_j \mid x_{t-1}^{(i)}, u_{t-1})
\end{aligned}
$$



Particle distribution typically observed during mapping

Adaptive Resampling

Effective Sample Size

$$N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N} \left(\tilde{w}^{(i)}\right)^2},$$

N_{eff} can be regarded as a measure of the dispersion of importance weights.

Each time N_{eff} drops below the threshold $N/2$ resampling is needed.

Require:

$\mathcal{S}_{t-1}$, the sample set of the previous time step

z_t, the most recent laser scan

u_{t-1}, the most recent odometry measurement

Ensure:

$\mathcal{S}_t$, the new sample set

$\mathcal{S}_t = \{\}$

for all $s_{t-1}^{(i)} \in \mathcal{S}_{t-1}$ **do**

$< x_{t-1}^{(i)}, w_{t-1}^{(i)}, m_{t-1}^{(i)} >= s_{t-1}^{(i)}$

// scan-matching

$x_t'^{(i)} = x_{t-1}^{(i)} \oplus u_{t-1}$

$\hat{x}_t^{(i)} = \text{argmax}_x \, p(x \mid m_{t-1}^{(i)}, z_t, x_t'^{(i)})$

if $\hat{x}_t^{(i)} =$ **failure then**

$x_t^{(i)} \sim p(x_t \mid x_{t-1}^{(i)}, u_{t-1})$

$w_t^{(i)} = w_{t-1}^{(i)} \cdot p(z_t \mid m_{t-1}^{(i)}, x_t^{(i)})$

else

// sample around the mode

for $k = 1, \ldots, K$ **do**

$x_k \sim \{x_j \mid |x_j - \hat{x}^{(i)}| < \Delta\}$

end for

// compute Gaussian proposal

$\mu_t^{(i)} = (0, 0, 0)^T$

$\eta^{(i)} = 0$

for all $x_j \in \{x_1, \ldots, x_K\}$ **do**

$\mu_t^{(i)} = \mu_t^{(i)} + x_j \cdot p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_t \mid x_{t-1}^{(i)}, u_{t-1})$

$\eta^{(i)} = \eta^{(i)} + p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_t \mid x_{t-1}^{(i)}, u_{t-1})$

end for

$\mu_t^{(i)} = \mu_t^{(i)} / \eta^{(i)}$

$\Sigma_t^{(i)} = \mathbf{0}$

for all $x_j \in \{x_1, \ldots, x_K\}$ **do**

$\Sigma_t^{(i)} = \Sigma_t^{(i)} + (x_j - \mu^{(i)})(x_j - \mu^{(i)})^T \cdot$
$p(z_t \mid m_{t-1}^{(i)}, x_j) \cdot p(x_j \mid x_{t-1}^{(i)}, u_{t-1})$

end for

$\Sigma_t^{(i)} = \Sigma_t^{(i)} / \eta^{(i)}$

// sample new pose

$x_t^{(i)} \sim \mathcal{N}(\mu_t^{(i)}, \Sigma_t^{(i)})$

// update importance weights

$w_t^{(i)} = w_{t-1}^{(i)} \cdot \eta^{(i)}$

end if

// update map

$m_t^{(i)} = \text{integrateScan}(m_{t-1}^{(i)}, x_t^{(i)}, z_t)$

// update sample set

$\mathcal{S}_t = \mathcal{S}_t \cup \{< x_t^{(i)}, w_t^{(i)}, m_t^{(i)} >\}$

end for

$N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N} (\tilde{w}^{(i)})^2}$

if $N_{\text{eff}} < T$ **then**

$\mathcal{S}_t = \text{resample}(\mathcal{S}_t)$

end if

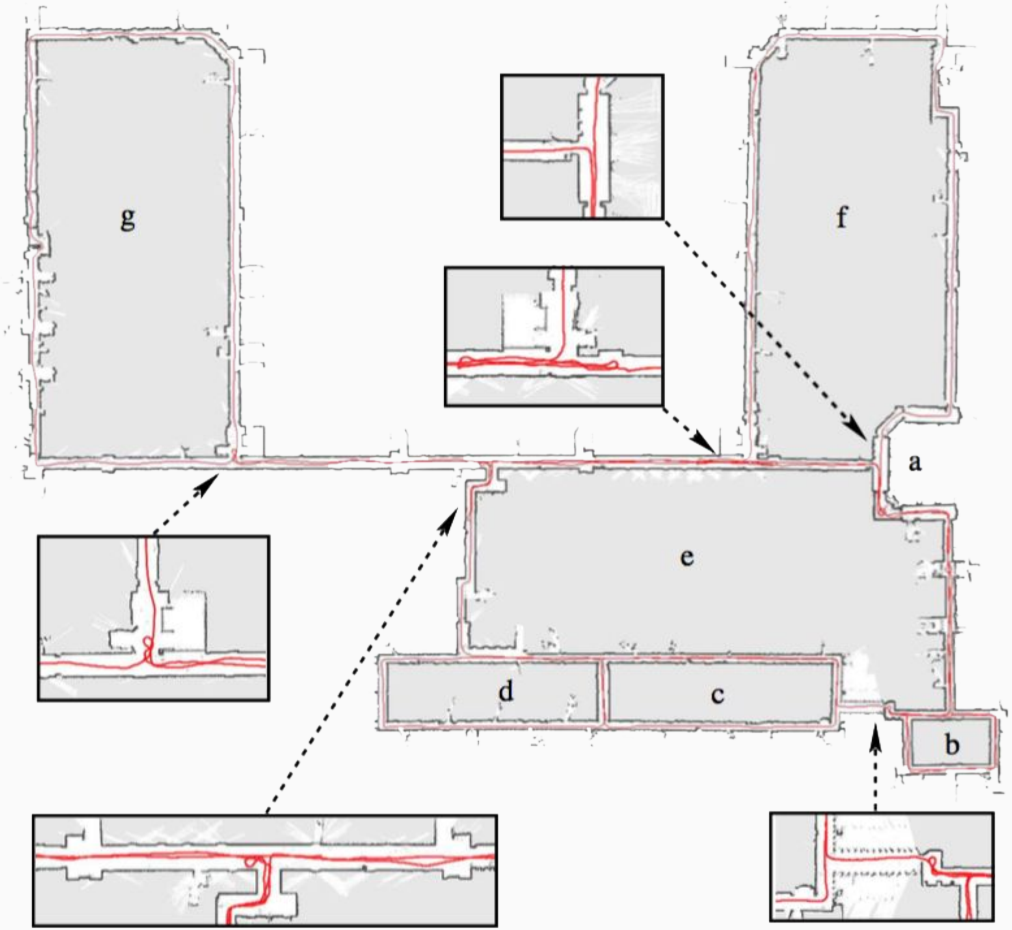
Complexity

Operation	Complexity
Computation of the proposal distribution	$O(N)$
Update of the grid map	$O(N)$
Computation of the weights	$O(N)$
Test if resampling is required	$O(N)$
Resampling	$O(NM)$

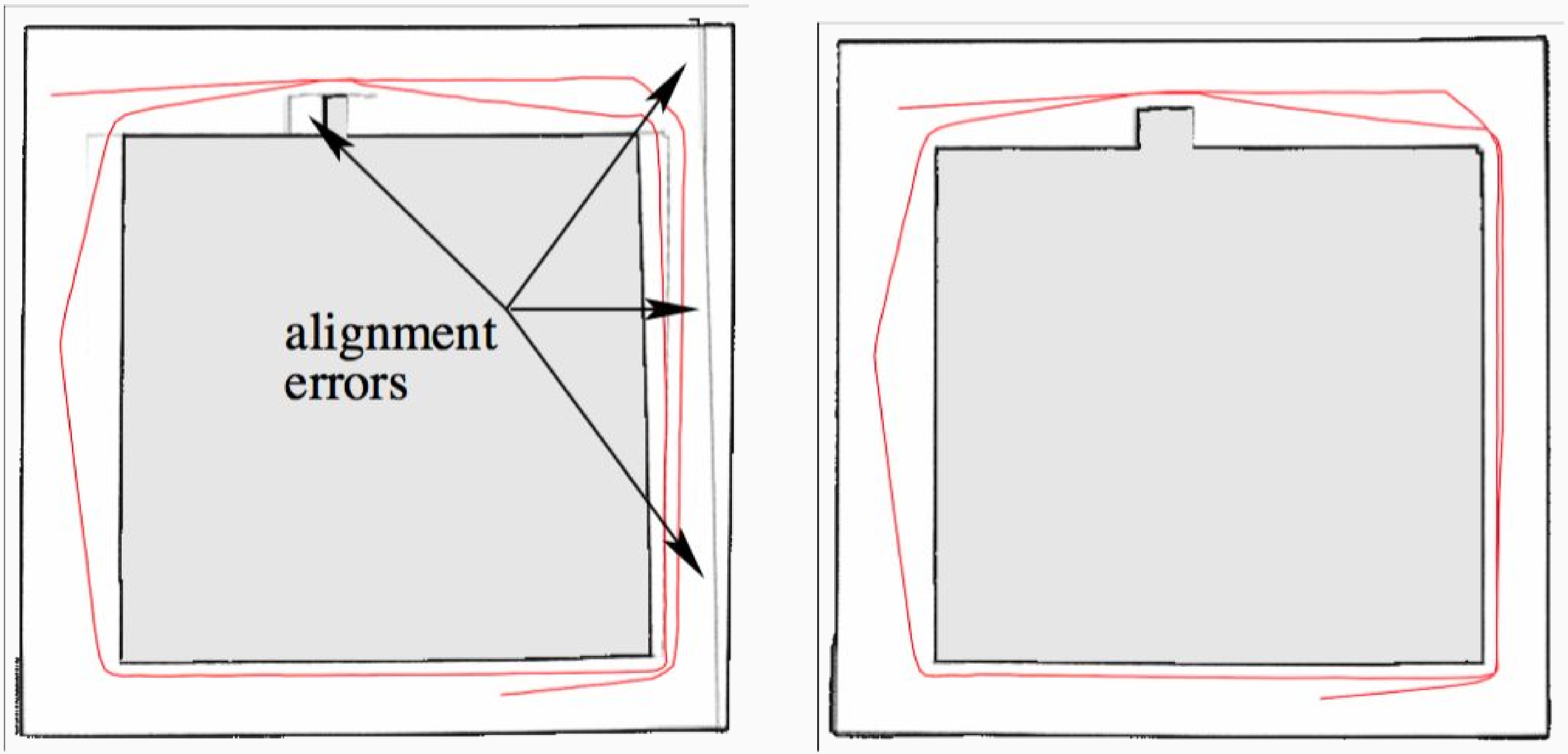
Different types of robots used(ActivMedia Pioneer 2 AT, Pioneer 2 DX-8, iRobot B21r)

The Intel Research Lab

The Freiburg Campus



The MIT Killian Court



Comparison to a prior work

References

G. Grisetti, C. Stachniss, and W. Burgard. Improved Techniques for Grid Mapping with Rao-Blackwellized Particle Filters, Robotics, IEEE Transactions on, 2007.

Thanks for listening!