Mapping and Localization with RFID Technology

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Outline

- Introduction
- Related Work
- Probabilistic Sensor Model
- Mapping
- Localization
- Experimental Results
- Conclusion
Introduction

- RFID - Radio Frequency Identification; One of the methods of AIDC
- Listen to broadcasts from receiver, reply with unique identifier
- Paper discusses using RFID technology to enhance localization
- Mobile robot equipped with laser scanner and RFID antennas used for experiment
- Sensor model to detect tag position (approximate) wrt any one antenna and repeated with antennae on mobile robot
Introduction

- Laser range data provides for map information
- Monte Carlo localization used for robot pose estimation
- RFID tags help reduce time and number of samples required for global localization
- Paper discusses using sensor model for RFID receivers with FastSLAM to localize RFID tags
- Suggests the use of these tags to detect positions of robots and people
Monte Carlo localization

- **Input** - 
  
  (sample),

- **Update motion and**

- **Resample and**

<table>
<thead>
<tr>
<th>Algorithm MCL($X_{t-1}, u_t, z_t$):</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{X}_t = X_t = \emptyset$</td>
</tr>
<tr>
<td>for $m = 1$ to $M$:</td>
</tr>
<tr>
<td>$x_t^{[m]} = \text{motion_update}(u_t, x_{t-1}^{[m]})$</td>
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<tr>
<td>$w_t^{[m]} = \text{sensor_update}(z_t, x_t^{[m]})$</td>
</tr>
<tr>
<td>$\bar{X}_t = \bar{X}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$</td>
</tr>
<tr>
<td>endfor</td>
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<tr>
<td>for $m = 1$ to $M$:</td>
</tr>
<tr>
<td>draw $x_t^{[m]}$ from $\bar{X}_t$ with probability $\propto w_t^{[m]}$</td>
</tr>
<tr>
<td>$X_t = X_t + x_t^{[m]}$</td>
</tr>
<tr>
<td>endfor</td>
</tr>
<tr>
<td>return $X_t$</td>
</tr>
</tbody>
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- calculate beliefs
Related Work

- RFID sensors have entered the field of mobile robotics
- Low-cost passive tags with long range help in navigation, localization, mapping etc
- Active beacons by Kantor and Singh to provide information based on tag response time
- Tsukiyama’s system does not deal with uncertainties
- SLAM techniques cannot be directly applied for range or bearing or both
Probabilistic Sensor Model

- Localization of tags based on a recursive update rule

\[ p(x \mid z_{1:t}) = \alpha p(z_t \mid x)p(x \mid z_{1:t-1}) \]  

- \( x \) = tag pose, \( z_{1:t} \) = data gathered in time \( t \), \( p(z_t \mid x) \) = likelihood of observation of \( z_t \) given \( x \)

- Considerations while designing observation model:
  - false negative readings
  - false positive readings
Probabilistic Sensor Model

Reasons for considerations:

- Orientation of tag wrt receiver influences signal energy
- Less energy might not power the chip inside the tag leading to a no-response
- Shape and size of detection range depend on environment

Observation model must cover such situations and ensure minimal errors in localization

Observation model determined by counting frequency of detections of tag wrt antennae on robot

Distance varied between tag and robot to get the map
Mapping

- First application of model is to localize tags
- Two steps to learn positions:
  - Learn geometric structure of environment using laser range sensor
  - Estimate tag position based on robot path
- Geometrical structure found using FastSLAM algorithm
- Use map and maximum likelihood path of robot to locate tags
- Apply the recursive Bayesian filtering scheme of Eq. 1
Mapping

- Pose belief of tag represented by a set of 1000 random positions uniformly distributed in a 25 m² area around robot’s current pose
- Area independent of antenna
- Initialization done at first detection of tag by robot
- Posterior probability assigned to each tag position corresponding to true pose of tag
- Posterior updated on each detection
**Localization**

- Compute likelihood of observation ‘y’ during localization knowing the posterior distributions of tag positions and given robot/person at position ‘l’

\[
p(y \mid l) = \sum_x p(y \mid r(x, l)) p(x \mid z_{1:t})
\]  

[Eq. 2]

- \(r(x, l)\) = position of tag relative to robot given pose ‘l’ of robot and location of tag sample ‘\(x\)’,
- \(p(y \mid r(x, l))\) = sensor model description
Localization

- recursive Bayesian filtering scheme:

\[
p(l_t \mid y_{1:t}, u_{0:t-1}) = \alpha \cdot p(y_t \mid l_t) \\
\cdot \int_{l'_{t-1}} p(l_t \mid u_{t-1}, l'_{t-1}) \cdot p(l'_{t-1} \mid y_{1:t-1}, u_{0:t-2}) \, dl'_{t-1}
\]

- \(\alpha = \) normalization constant, \(p(l_t \mid u_{t-1}, l'_{t-1}) = \) probability of object to be at \(l_t\) given it executed movement \(u_{t-1}\) at position \(l'_{t-1}\)
Localization

- In Monte Carlo localization, belief of robot is a set of random samples.
- Each sample consists of state vector which is pose of robot and weight factor ‘w’.
- Weight factor provides importance of particle.
- Beliefs updated on two alternating steps:
  - In prediction step, new sample for each sample based on weight and model probability of robot’s dynamics since previous update.
  - In correction step, new observation is integrated into sample set by bootstrap resampling.
- For RFID sensors, samples placed on in potential detection range of sensor.
Experimental Results

- Implementation and Testing done using Pioneer 2 robot with SICK LMS laser range-finder and Alien Technology’s 915 MHz RFID reader with two circularly polarized antennas

[Fig. 2]
Experimental Results

- Mapping RFID tags
  - Trajectory estimation by FastSLAM to determine posterior of tag location
  - On first detection, initialize random points around robot and use uniform distribution for belief
  - On tag detection, update posterior probability based on likelihood of observation
  - Normalize belief over all samples

[Fig. 7]
Experimental Results

- Mapping RFID tags
  - Representation can handle ambiguities in which location of tag can’t be determined uniquely
  - Algorithm can accurately localize tags
  - There is noise and a several false detections
  - Learn position of multiple tags in environments

[Fig. 10]
Experimental Results

- Localization with RFID tags
  - Robot steered through environment and Monte Carlo localization applied to globally estimate position
  - Person localization done by ignoring odometry data and changing motion model in Monte Carlo localization
  - Motion model of robot replaced by Gaussian distribution centered around current pose of robot to approximate motion of person

[Fig. 9]
Experimental Results

- Improving Global Localization with RFID tags
  - RFID technology can be used to improve global localization even when highly accurate sensors are used
  - Use of RFID sensors reduce the number of samples required
  - Motion model of robot replaced by Gaussian distribution centered around current pose of robot to approximate motion of person

[Fig. 11]

[Fig. 12]
Conclusion

- Generated maps of RFID tags with mobile robots
- Sensor model to compute likelihood of tag detections
- Use of posteriors to localize robot/people
- Showed that maps can be used to localize robots without odometry data
- Reduce computational demands for localization by using RFID technology with laser scanners
Opinion

- Good paper providing proof of concept with good experimental results
- Well documented; makes it easier to re-perform and compare results
- Could have explained certain algorithms and math in detail
- As a panelist, I would accept this paper
Questions?