Mapping and Localization with RFID Technology

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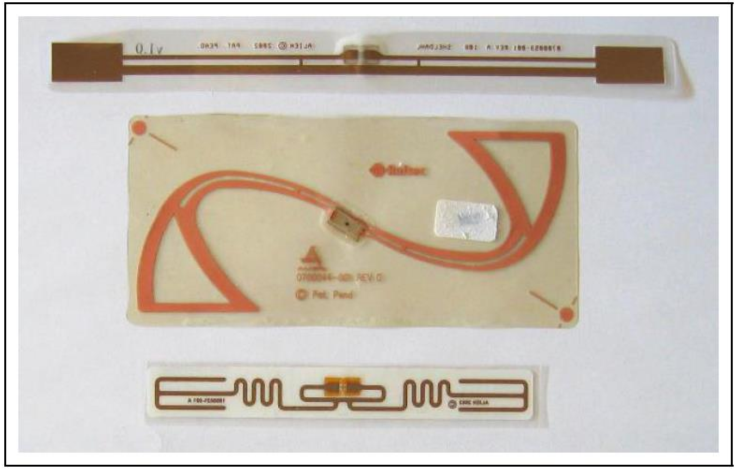
Outline

- ❑ 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



[Fig. 1]

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 tas to detect positions of robots and people

Monte Carlo localization

- Input -

  (sample),

  sensor

- Update motion and

- Resample and

Algorithm MCL(X_{t-1}, u_t, z_t):

$\quad \bar{X}_t = X_t = \emptyset$

$\quad$ for $m = 1$ to M:

$\qquad x_t^{[m]} =$ motion_update$(u_t, x_{t-1}^{[m]})$

$\qquad w_t^{[m]} =$ sensor_update$(z_t, x_t^{[m]})$

$\qquad \bar{X}_t = \bar{X}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$

$\quad$ endfor

$\quad$ for $m = 1$ to M:

$\qquad$ draw $x_t^{[m]}$ from $\bar{X}_t$ with probability $\propto w_t^{[m]}$

$\qquad X_t = X_t + x_t^{[m]}$

$\quad$ endfor

$\quad$ return X_t

calculate beliefs

based on probability

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

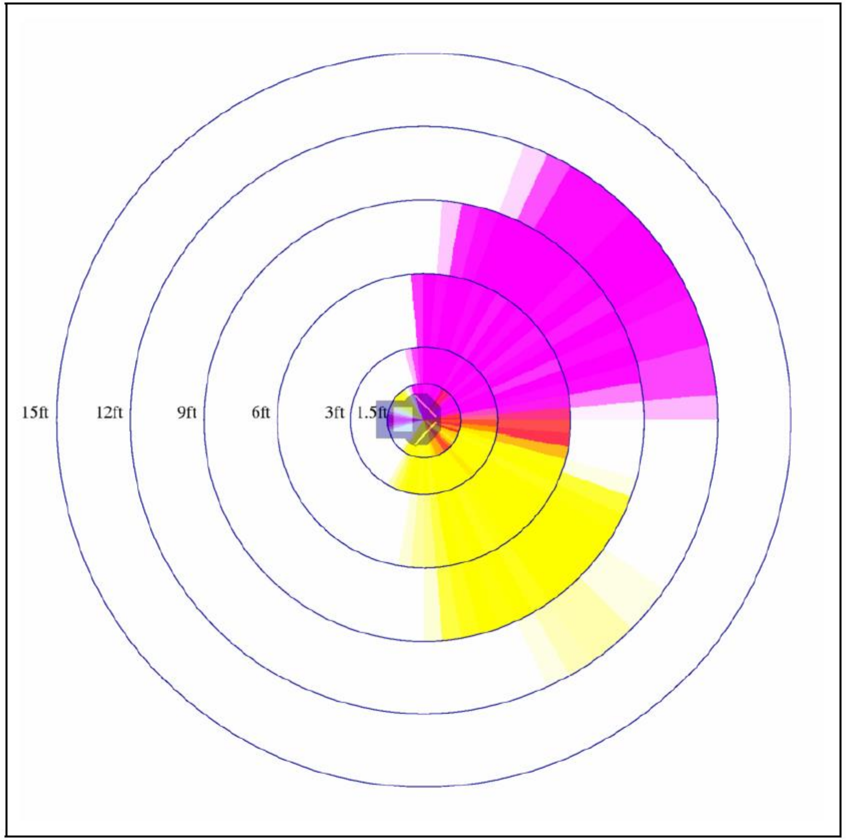
- Localization of tags based on a recursive update rule

$$p(x \mid z_{1:t}) \quad = \quad \alpha p(z_t \mid x) p(x \mid z_{1:t-1}) \qquad \text{[Eq. 1]}$$

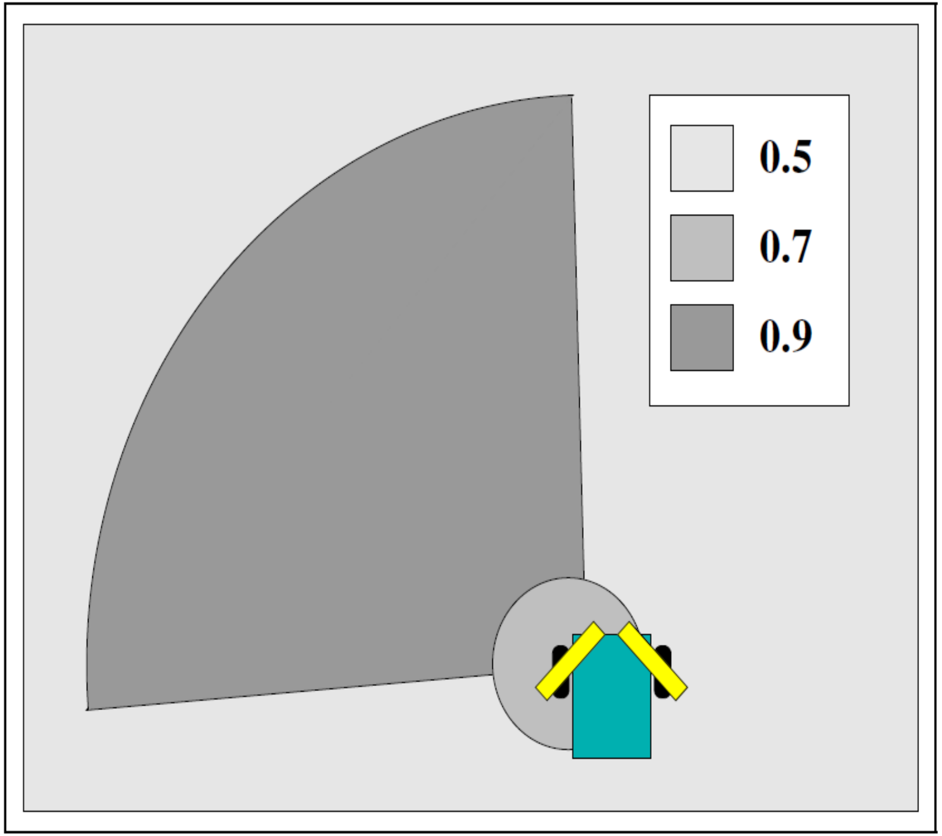
- x = tag pose, $z_{1:t}$ = data gathered in time t, $p(z_t \mid x)$ =likelihood of observation of z_t given x
- Considerations while designing observation model:
    - false negative readings
    - false positive readings

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



[Fig. 3]



[Fig. 4]

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 m^2 are 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'

$$p(y \mid l) = \sum_x p(y \mid r(x, l))p(x \mid z_{1:t}) \quad \text{[Eq. 2]}$$

- ❑ r(x,l) = position of tag relative to robot given pose 'l' of robot and location of tag sample 'x', p(y | r(x,l)) = sensor model description

Localization

- recursive Bayesian filtering scheme:

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

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

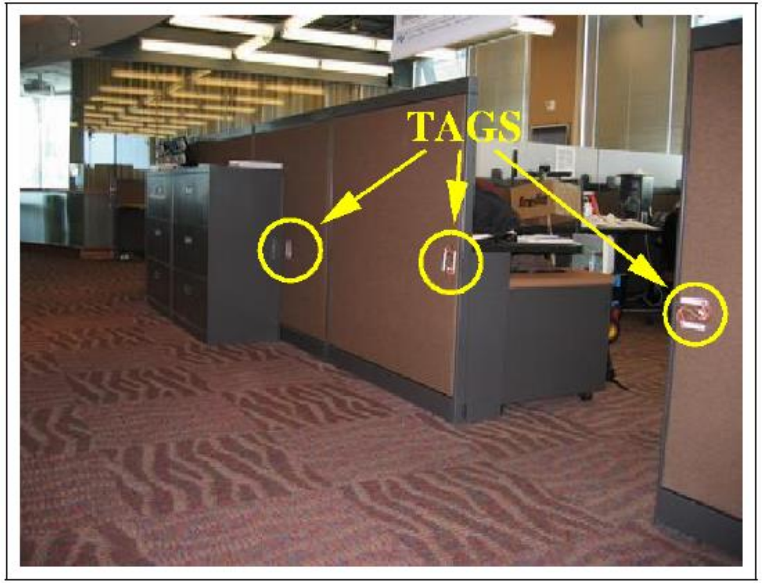
Localization

- 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

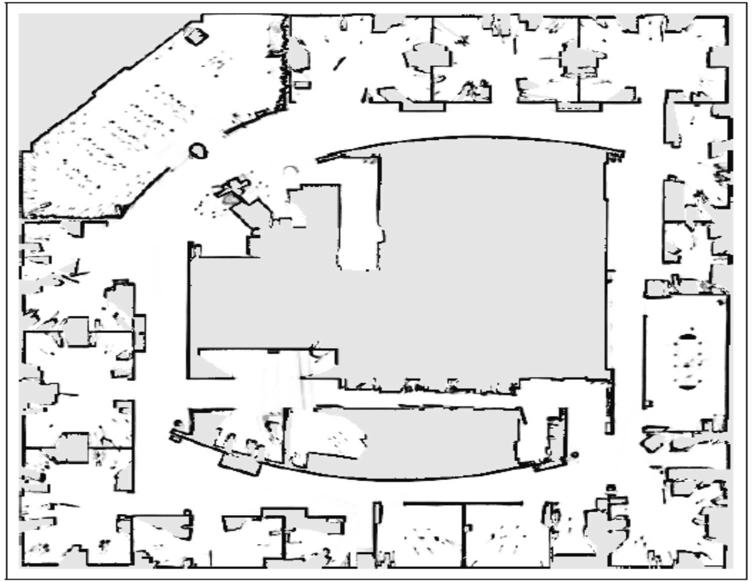
Experimental Results

- 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]



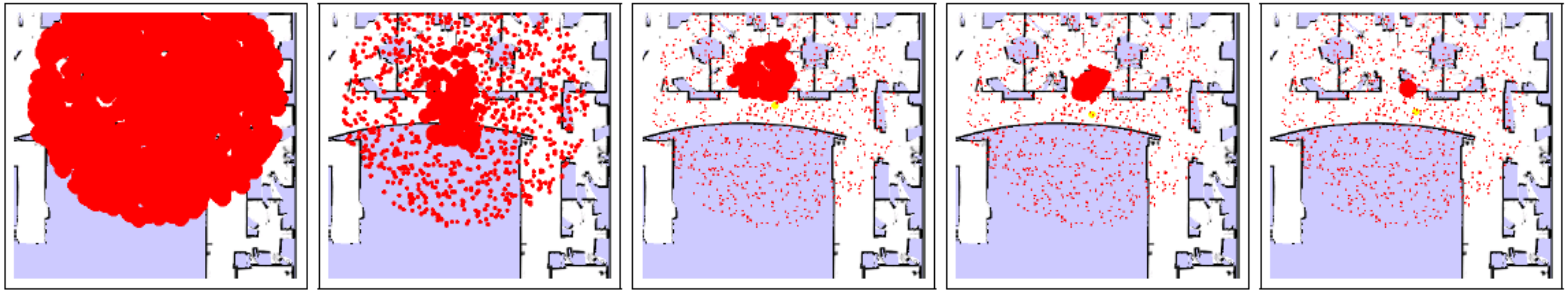
[Fig. 6]



[Fig. 7]

Experimental Results

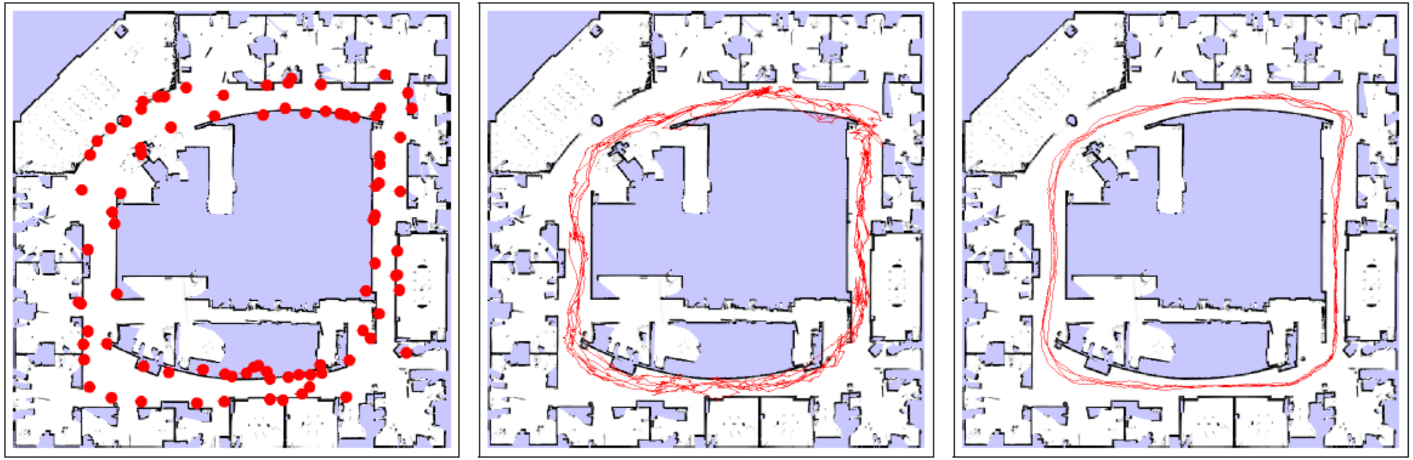
- ❑ Mapping RFID tags
  - ❑ Trajectory estimation by FastSLAM to determine posterior of toag location
  - ❑ On first detection, initialize random points around robot and use uniform distribution for belief
  - ❑ On tag detection, update posterior probability based on likelihood of observation
  - ❑ Normalize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



[Fig. 7]

Experimental Results

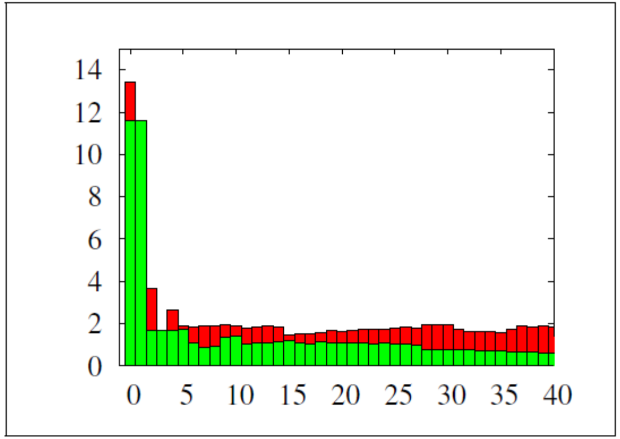
- ❑ Mapping RFID tags
  - ❑ Representation can handle ambiguities in which location of tag can’t be determined uniquely
  - ❑ Algorithm can accurately localize tags
  - ❑ There is noise and a several false detections
  - ❑ Learn position of multiple tags in environments



[Fig. 10]

Experimental Results

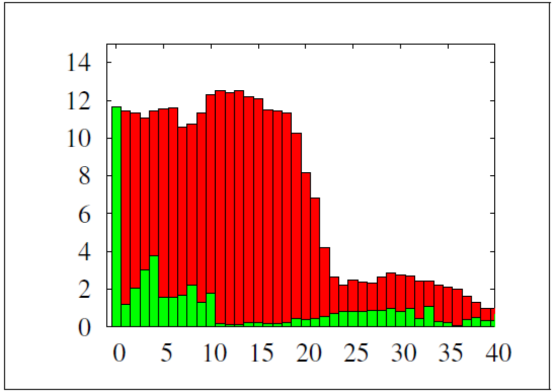
- Localization with RFID tags
  - Robot steered through environment and Monte Carlo localization applied to globally estimate position
  - Person localization done by ignoring odometry data and changing motion model in Monte Carlo localization
  - Motion model of robot replaced by Gaussian distribution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



[Fig. 9]

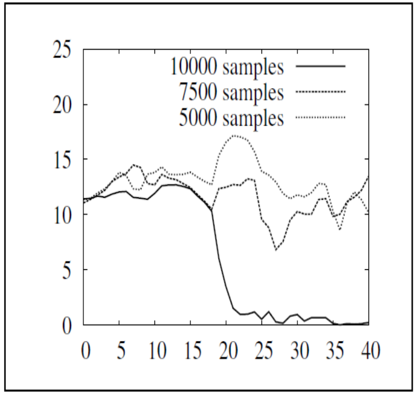
Experimental Results

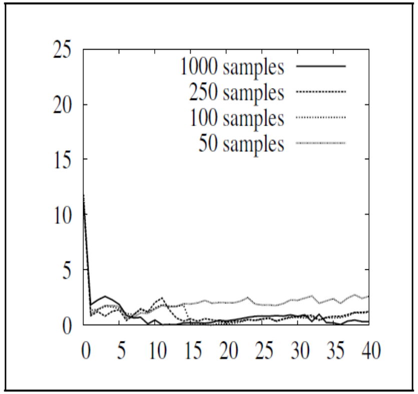
- Improving Global Localization with RFID tags
  - RFID technology can be used to improve global localization even when highly accurate sensors are used
  - Use of RFID sensors reduce the number of samples required
  - Motion model of robot replaced by Gaussian distribution centered around current pose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