Practical Vision-Based Monte Carlo Localization on a Legged Robot

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Department of Computer Scienes
The University of Texas at Austin

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The Problem

**Mobile Robot Localization**

Maintain *estimate* of global *position* and *orientation* over time

- Given *map* of fixed landmark locations
- Not SLAM
The Problem

Mobile Robot Localization

Maintain estimate of global position and orientation over time

- Given map of fixed landmark locations
- Not SLAM
Challenging Platform

Typical Platform

- Wheeled robot
- Range-finding sensors

Sony Aibo ERS-7

- Color CMOS Camera in nose
  - Narrow field-of-view (56°)
  - 30 YCrCb frames per second
- Quadruped
- 576MHz processor
  - All on-board processing
Our Platform

- Legged robot
- Vision-based sensors

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- 576MHz processor
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Goal

Desiderata
- Navigate to **specific point** quickly
- Remain localized while **colliding**
- Recover quickly from **kidnappings**

Approach
- Begin with **baseline MCL algorithm**
- Add set of practical **enhancements**

*Large improvement over baseline*
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Large improvement over baseline
Method: Particle Filtering

- Estimate \( p(h_T | o_T, a_{T-1}, o_{T-1}, a_{T-2}, \ldots, a_0) \): Distribution of poses given observations and actions
- Represented by finite set of samples: particles
  - Each is a hypothesis: \( \langle \langle x, y, \theta \rangle, p \rangle \)
- Average to get single estimate of pose and confidence
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Outline

1. Practical Enhancements
   - Distance-Based Updates
   - Landmark Histories
   - Extended Motion Model

2. Empirical Results
   - Physical Robot Experiments
   - Simulation Experiments
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Baseline: Observation Update

- **Need sensor model:** $p(o|h)$
  - Predicts observations given pose hypothesis using map
- **Update each particle when robot sees something**
  - Compute similarity for each observed landmark in frame
    - Use angles only [Rofer and Jungel, 2003]
    - Measured and expected angle difference
  - Compute product of similarities
  - Adjust probability closer to new value
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![Graph showing similarity versus angle difference](image)

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<tr>
<td></td>
<td>0</td>
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<tr>
<td>0.504</td>
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<td>0.7</td>
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Enhancement: Distance-Based Updates

- **Enhancement to observation update**
  - Use *distance* in addition to *angle*
  
- Update each particle
  - Difference between measured and expected distance
  - Use average of distance and angle similarities

- Distances must be very accurate
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- Know actual height of beacon and focal length of camera
- Measure height of beacon in image
- Use similar triangles to find distance
- Error due to pixelized segmentation, distortion, etc.
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Function Approximation

- Place robot at **known distances**
- Actual and Measured don’t match (Nonlinear relationship)
- Approximate function using cubic regression for each landmark
- Maximum error reduced to 5%

![Graph showing measured vs. actual distances with a linear regression line.]
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![Graph showing approximated function]

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**Result**

Distances safe to use.
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   - Physical Robot Experiments
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Baseline: Reseeding

Based on **Sensor Resetting MCL** [Lensér et al., 2000]

- Helps **recovery when lost**
- Triangulate position using multiple landmarks
  - Three landmarks using just **angles**
  - Two landmarks using **distances** and **angles**
- Add new hypotheses before resampling step
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Shortcoming

- Robot must see multiple landmarks in the same frame
- Infrequent with narrow field-of-view camera
Enhancement: Landmark Histories

- Want **more reseeding values**
  - Maintain **“history”** of recent observations
- Observation list for each landmark
  - Record: Dist, Ang, Conf, Timestamp, Odometer
- Motion update
- Confidence decay
- Remove old
- Weighted average
- Combine for reseed
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**Problem**

- **Tradeoff between speed and motion model accuracy**
  - Large steps over small distances inaccurate
  - Unable to navigate to specific point

**Solution: Change Behavior**

- Use accurate but slower walk near target
  - Step size reduced to 10% within 300mm of target
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Test for Accuracy and Time

- **Environment**: RoboCup Legged League field
  - Size: roughly $3m \times 5m$
  - Landmarks: 4 beacons, 4 goal edges
- Visit sequence of 14 points and headings
- After stabilizing at a point, measure
  - Time taken
  - Position and orientation error
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![Diagram of RoboCup Legged League field with visit sequence of 14 points and headings.](image-url)
Test for Accuracy and Time

Six Localization Conditions

1. Baseline (None)
2. Landmark Histories (HST)
3. Distance-based probability updates (DST)
4. Function approximation of distances (FA)
5. Function approx. + distance-based updates (FA+DST)
6. All enhancements (All)

- Extended Motion Model present in all
- Average across 10 runs for each
Test for Accuracy and Time

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- **With all enhancements**
  - 50% reduction in position error
  - 80% reduction in orientation error
  - No significant change in time
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<tbody>
<tr>
<td>None</td>
<td>19.75±12.0</td>
<td>17.75±11.48</td>
<td>161.25±3.43</td>
</tr>
<tr>
<td>HST</td>
<td>17.92±9.88</td>
<td>10.68±5.97</td>
<td>161.26±5.96</td>
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<tr>
<td>DST</td>
<td>25.07±13.73</td>
<td>9.14±5.46</td>
<td>196.18±12.18</td>
</tr>
<tr>
<td>FA</td>
<td>15.19±8.59</td>
<td>10.21±6.11</td>
<td>171.85±15.19</td>
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<tr>
<td>DST+FA</td>
<td>13.72±8.07</td>
<td>9.5±5.27</td>
<td>151.28±48.06</td>
</tr>
<tr>
<td>All</td>
<td>9.65±7.69</td>
<td>3.43±4.49</td>
<td>162.54±4.38</td>
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- Additional findings
  - Bad distance updates hurt (25% increase in error)
  - Func. Approx. largest contributor
  - Combined better than in isolation
Test for Stability

- Test ability to **stay localized** once at target
- Robot **stationary** at each of 14 points

1. Attempt to localize for 10 seconds
2. Record deviation of pose estimate for 20 seconds
Test for Stability

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<tr>
<td>None</td>
<td>2.63</td>
<td>0.678</td>
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<tr>
<td>HST</td>
<td>1.97</td>
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<tr>
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- Significant improvement in stability
- Bad distance updates again perform worst
- Func. Approx. alone does as well as All
  - Distance information useful in reseed estimates
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Test impact of extended MM in isolation
Evaluate ability to navigate to a point
  Used “keeper” home position
  Displace robot by hand a fixed distance
  Allow to return to home position
  Measure position and orientation error and time

Average of ten runs
### Results

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- 40% reduction in position error
- 60% reduction in orientation error
- Only a small increase in time
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Outline

1 Practical Enhancements
   - Distance-Based Updates
   - Landmark Histories
   - Extended Motion Model

2 Empirical Results
   - Physical Robot Experiments
   - Simulation Experiments
Simulator

- Abstract noisy observations and movements
- Always know ground truth
- Perturbations repeatable
Test for Recovery

- Robot follows **figure 8** path
  - **Perturbed** once every 30 seconds
- Two types of interference
  - **Collisions** (stop for 5s)
  - **Kidnappings** (teleported 1.2m)
- **Measure** position and angle error on subset of conditions
  - Averaged over 2 hours (about 50 laps)
Robot follows **figure 8** path
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<td>8.03</td>
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- As expected, performance worse in presence of perturbations
- Enhancements mitigate performance degradation
  - Over 900% error increase for kidnappings without enhancements
  - Reduced to 56% increase with all enhancements
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Summary

- Monte Carlo Localization works well in theory
- Practical implementation issues
  - Especially using vision-based legged robots
- Three Enhancements
  - Significant improvement over baseline
  - More dramatic for unmodeled movements
- Help others avoid potential pitfalls