Practical Vision-Based Monte Carlo Localization on a Legged Robot

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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

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Challenging Platform

Typical Platform

- Wheeled robot
- Range-finding sensors

Sony Aibo ERS-7

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

Challenging Platform

Our Platform

- Legged robot
- Vision-based sensors

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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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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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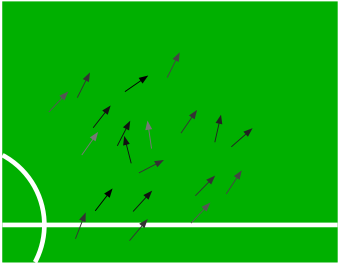

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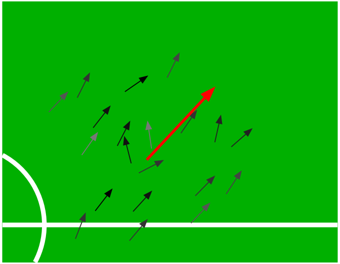

Outline

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: $p(o|h)$
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    - Use angles only [Rofer and Jungel, 2003]
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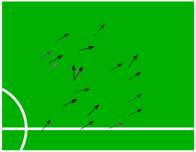

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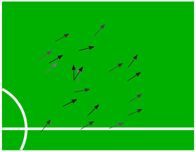

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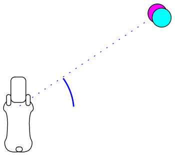

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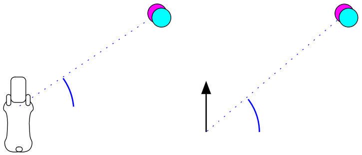

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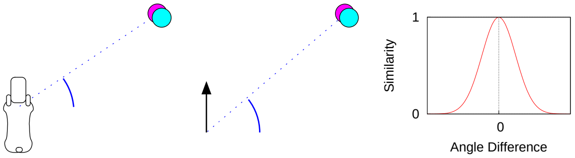

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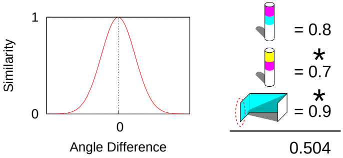

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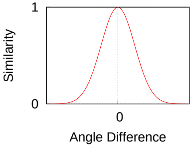

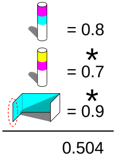

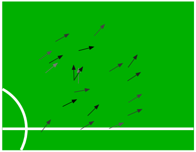

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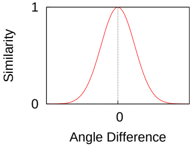

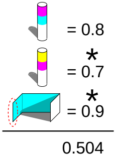

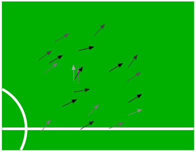

Enhancement: Distance-Based Updates

- Enhancement to observation update
  - Use distance in addition to angle
- Update each particle
  - Difference between measured and expected distance
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- Distances must be very accurate

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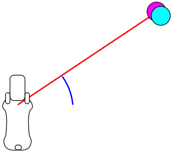

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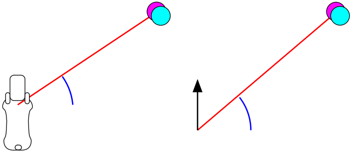

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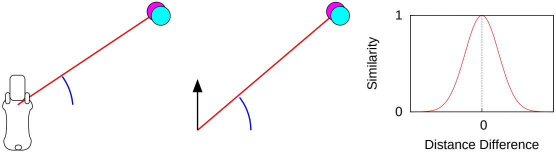

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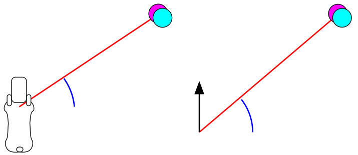

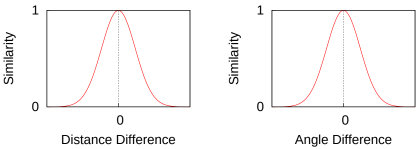

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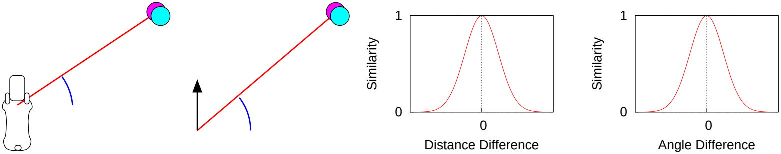
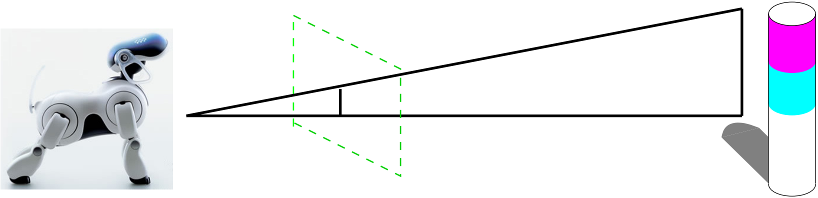


Estimating Landmark Distances

- 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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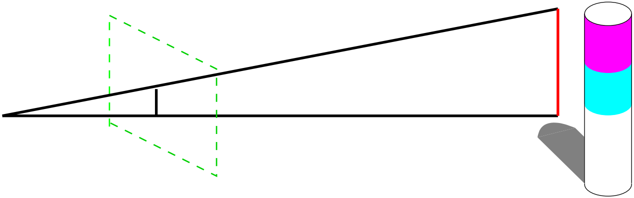

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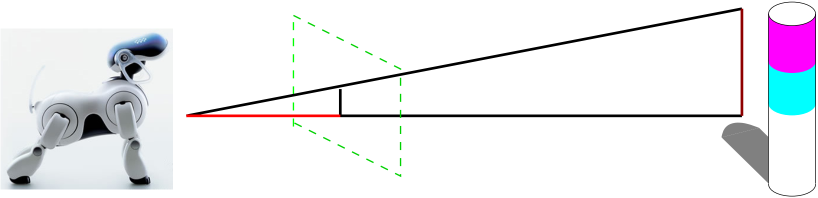

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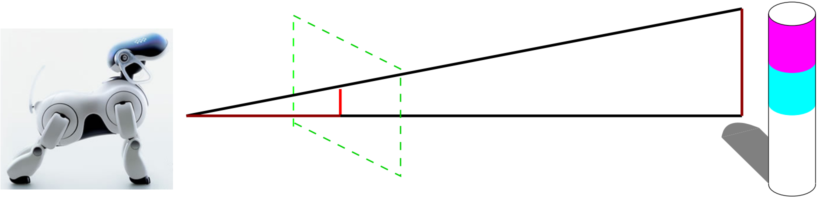

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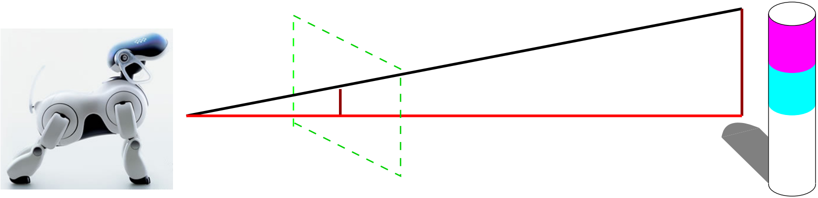

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- Place robot at known distances
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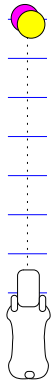
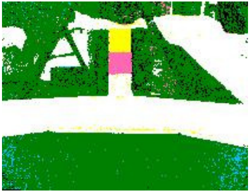
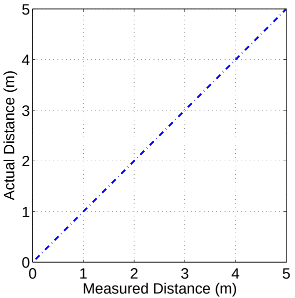
- Approximate function using cubic regression for each landmark
- Maximum error reduced to 5%







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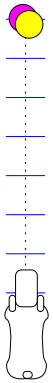

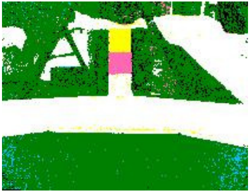

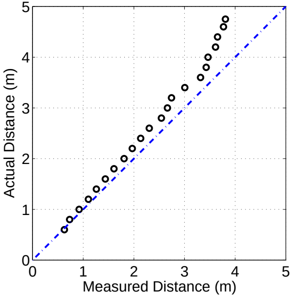

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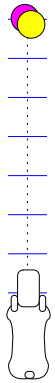

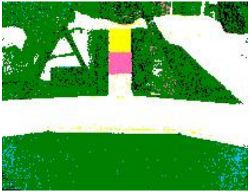

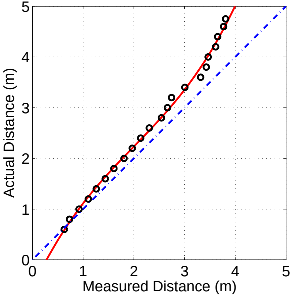

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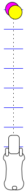

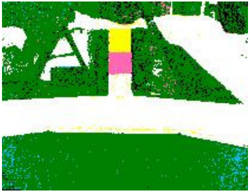

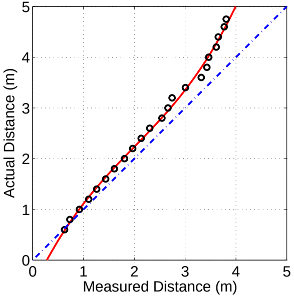

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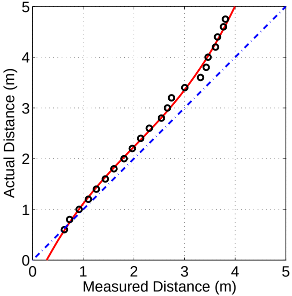
Result

Distances safe to use.



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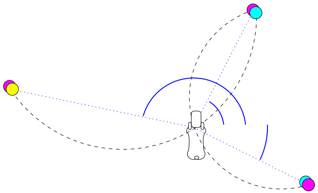

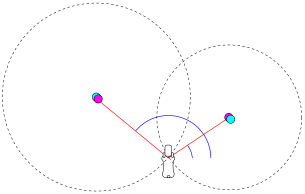

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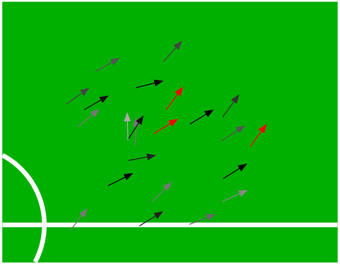

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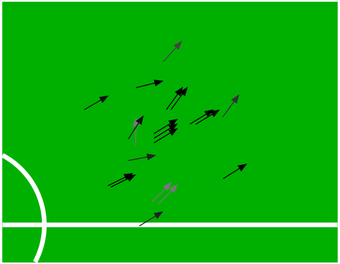

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Shortcoming

- 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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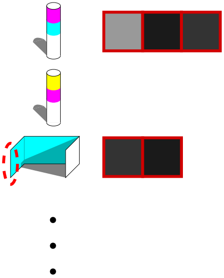

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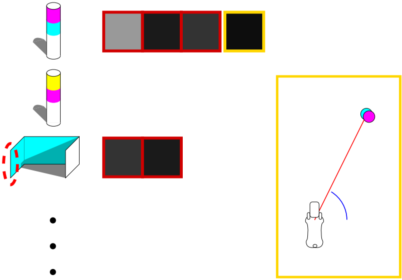

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- Confidence decay
- Remove old
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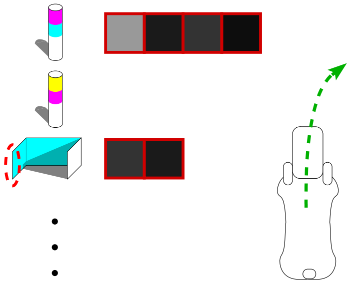
- Combine for reseed



Enhancement: Landmark Histories

- Want more reseeding values
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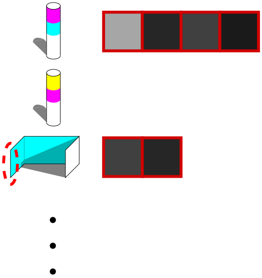

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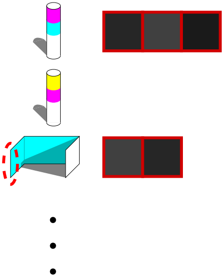

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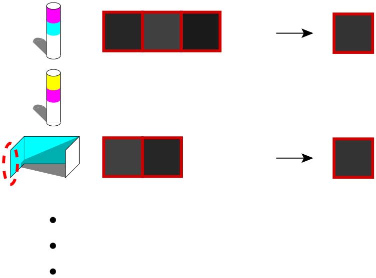

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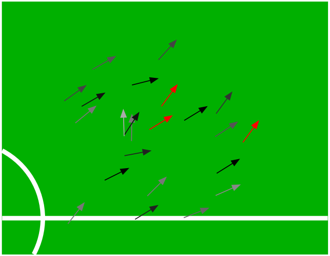

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- Need motion model: $p(h'|h, a)$
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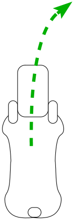

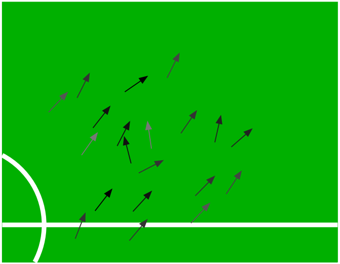

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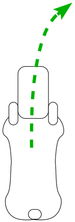

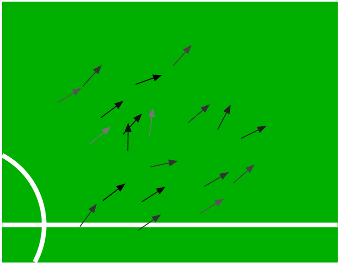

Enchancement: Extended Motion Model

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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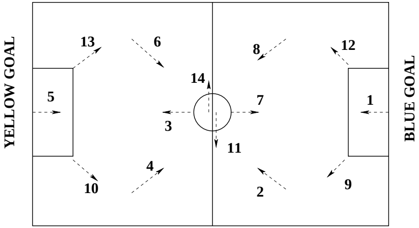
Test for Accuracy and Time

- 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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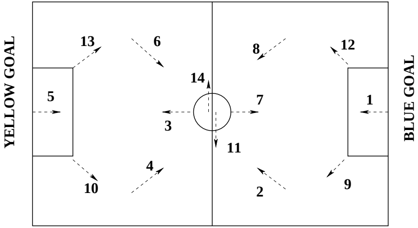

Test for Accuracy and Time

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

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Results

Enhan.	Dist Err (cm)	Ang Err (deg)	Total Time (s)
None	19.75±12.0	17.75±11.48	161.25±3.43
HST	17.92±9.88	10.68±5.97	161.26±5.96
DST	25.07±13.73	9.14±5.46	196.18±12.18
FA	15.19±8.59	10.21±6.11	171.85±15.19
DST+FA	13.72±8.07	9.5±5.27	151.28±48.06
All	9.65±7.69	3.43±4.49	162.54±4.38

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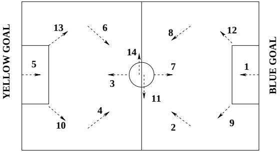
Test for Stability

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



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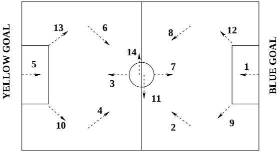

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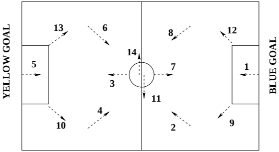

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Results

Enhan.	Dist Dev (cm)	Ang Dev (deg)
None	2.63	0.678
HST	1.97	0.345
DST	9.26	3.05
FA	1.46	0.338
DST+FA	4.07	1.30
All	1.32	0.332

- 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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Evaluating Extended Motion Model

- 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

Enhan.	Dist Err (cm)	Ang Err (deg)	Time (s)
None	12.89	15.0	17.21
Extended MM	7.50	5.5	18.14

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

Results

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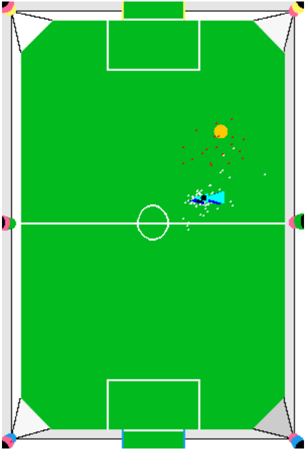
Simulator

- 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)

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Results

Enhan.	Distance Error (cm)		
	Undisturbed	Colliding	Kidnapped
None	8.03	27.7	74.3
HST	17.6	25.3	27.3
DST+FA	7.83	16.2	31.5
All	8.67	14.4	13.5

- As expected, performance worse in presence of perturbations
- Enhancements mitigate performance degradation
  - Over 900% error increase for kidnappings without 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