Negative Information and Line Observations for Monte Carlo Localization

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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

- Sony Aibo ERS-7
  - Color CMOS Camera in nose
    - Narrow field-of-view (56^o)
    - 30 YCrCb frames per second
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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 Negative Information
- Add Line Observations

Significant improvement over baseline

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Outline

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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: $\langle \langle x, y, \theta \rangle, p \rangle$
- Weighted average to get single estimate of pose and confidence

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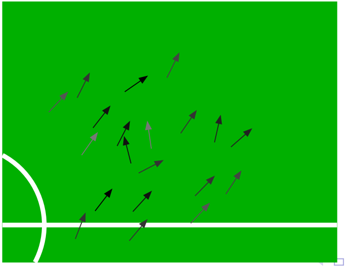

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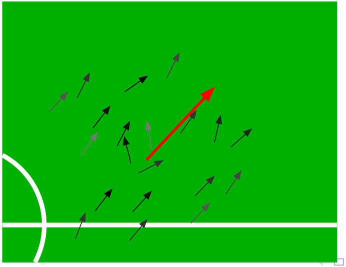

Observation Update

- 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 and distances to landmarks
    - Difference in measured and expected values
  - Compute product of similarities
  - Adjust probability closer to new value

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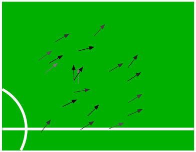

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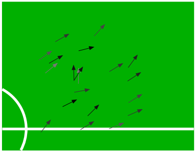

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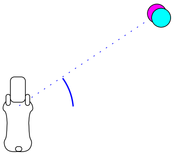

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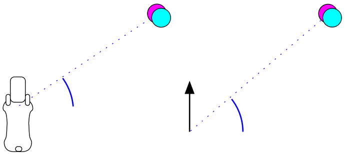

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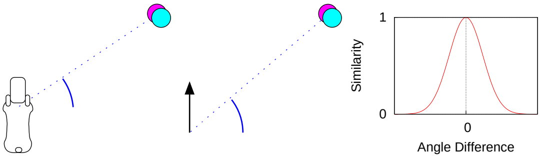

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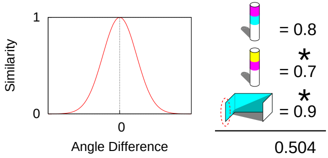

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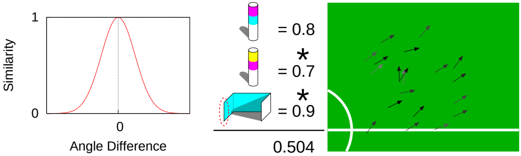

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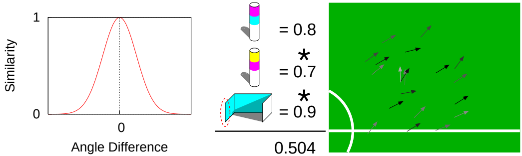
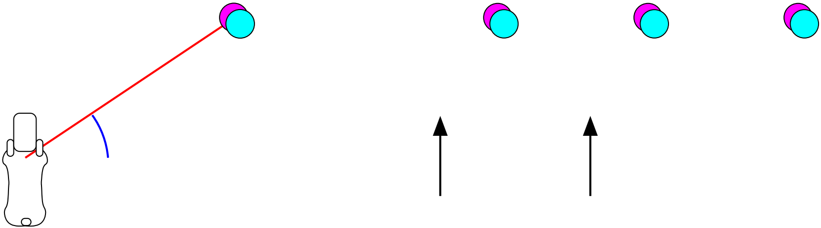


Ambiguous Landmarks

- What if the landmarks are ambiguous?
- Update each particle based on most likely landmark
  - Compute similarity for each possible landmark
  - Update particle using most likely landmark (most similar)



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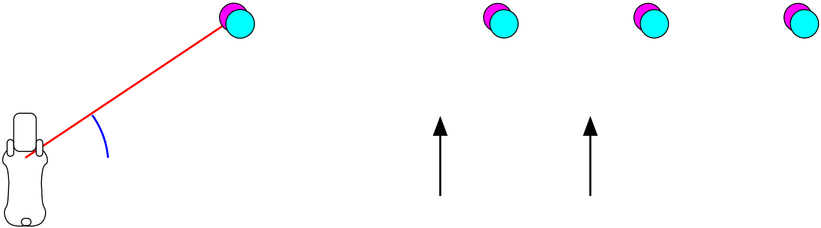

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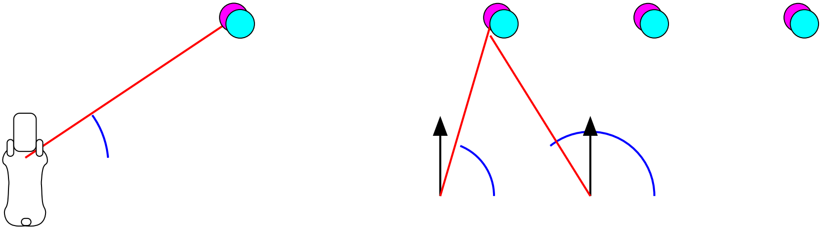

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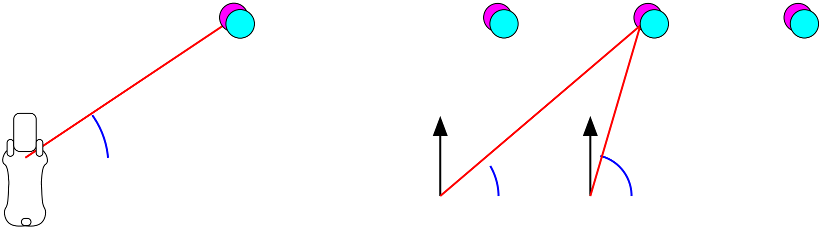

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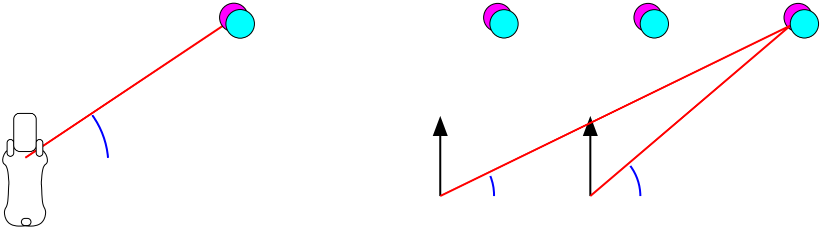

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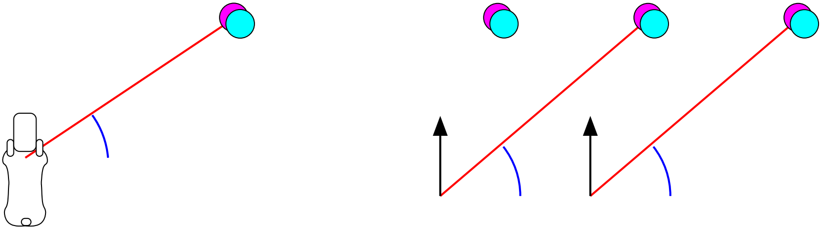
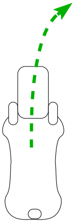
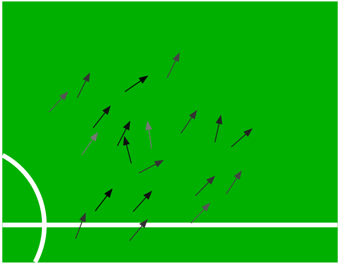


Motion Update

- Need motion model: $p(h'|h, a)$
  - Predict new pose given previous hypothesis and action
- Update each particle when robot moves
  - Use odometry velocities to translate particles





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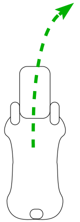
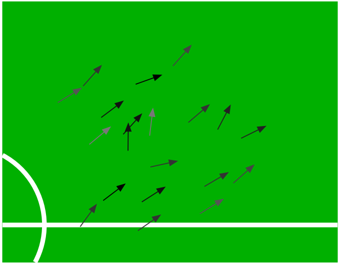
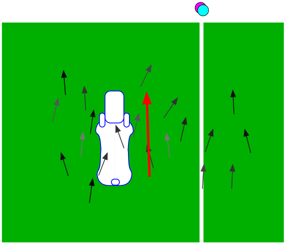




Outline

Negative Information

- Expect to see a landmark, but do not see it
- How it works
  - Particles expect to see a landmark
  - Robot does not see the landmark
  - Update the particles with a lower probability



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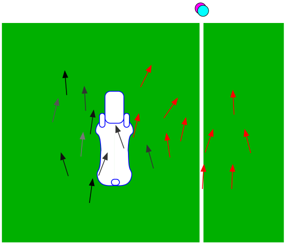

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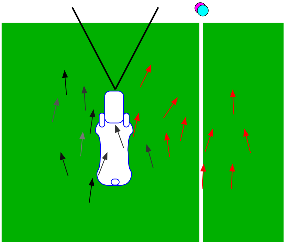

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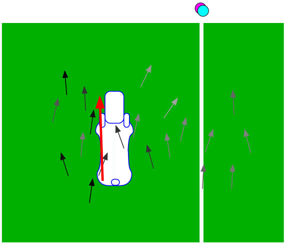

Previous work of Hoffmann et al

- For each particle, assume robot is at that particle's pose
  - For each landmark
    - Determine if landmark should be in field of view
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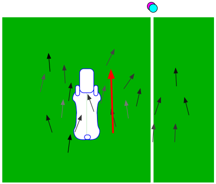

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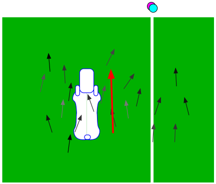

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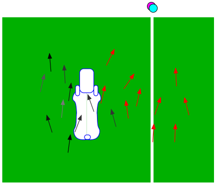

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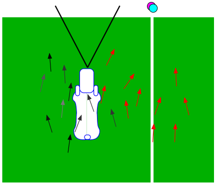

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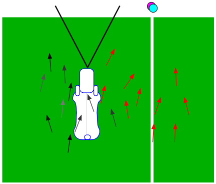

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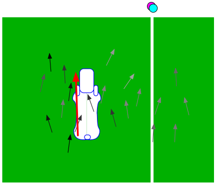

Our approach

- More robust to missed observations of landmarks that are in field of view
- For each particle and landmark
  - Keep counters of number of consecutive frames that:
    - The landmark has been expected to be seen
    - The landmark has not been
  - If both of these counters are over a threshold t,
    - Update particle with probability of missing t observations
- Generalizes Hoffmann et. al's approach
  - Equivalent with $t = 1$

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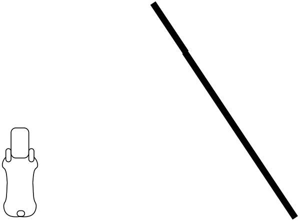
Line Observations

- How do we update the particles when we see a line?
  - Do not know where along the line we are
  - Provides information on distance and orientation to line



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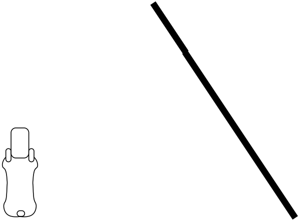

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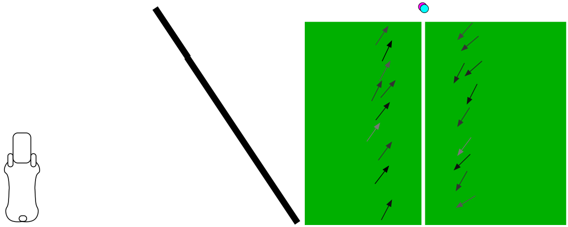
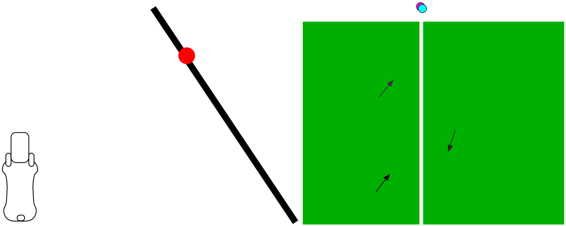


Our approach

- Find closest point on observed line
- Get distance and angle to this point
- Find closest point on line from particle pose
- Update using distance and angle as before
    - As if this were a point landmark



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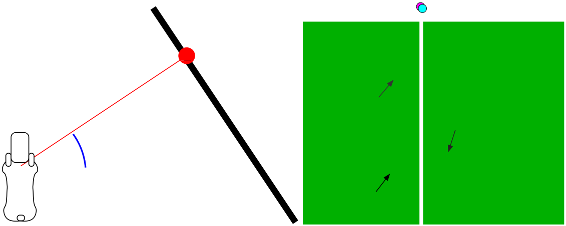

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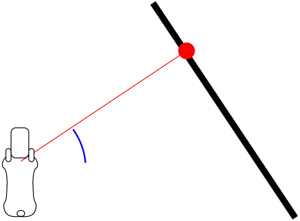

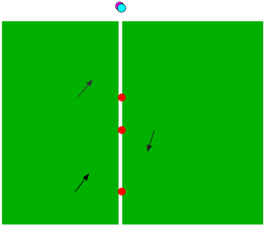

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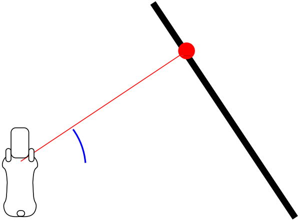

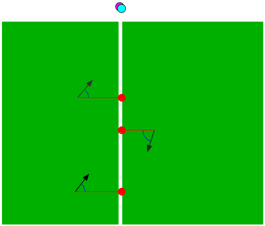

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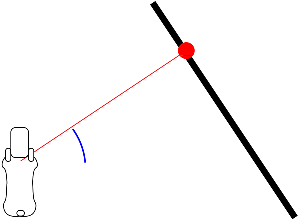
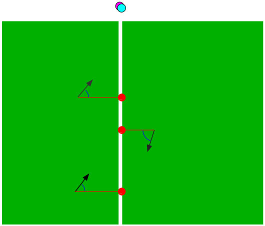


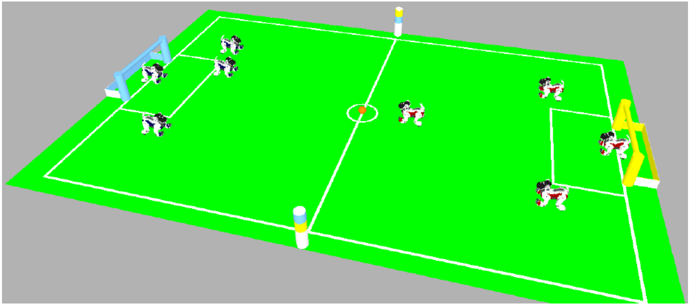


Outline

1. Introduction
   - Localization Problem
   - Particle Filtering
2. Enhancements
   - Negative Information
   - Line Observations
3. Empirical Results
   - Physical Robot Experiments
   - Simulation Experiments

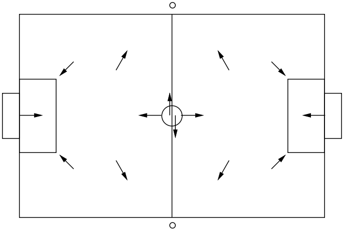
Environment

- RoboCup Legged League field
  - Size: roughly $3.6m \times 5.4m$
  - Landmarks: 2 beacons, 2 goals, 11 field lines



Localization Accuracy

- Visit sequence of 14 points and headings
- After stabilizing at a point, record
  - Actual position and orientation
  - Robot's belief of position and orientation
- Calculate error between actual and believed pose
- Significance results using one-tailed Student's t test



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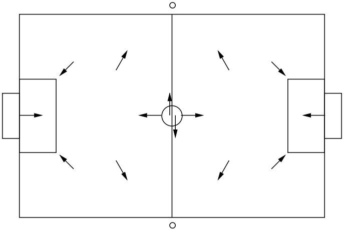

Localization Accuracy

Four Versions of Algorithm

1. Baseline (None)
2. Negative Information (NEG)
3. Line Observations (LINES)
4. Both enhancements (All)

- Average across 10 runs for each

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Algorithm	Distance Error(cm)	p-value	Angle Error(deg)	p-value
None	17.67	–	5.39	–
NEG	15.57	0.103	5.16	0.358
LINES	13.62	0.010	5.08	0.381
BOTH	13.38	0.014	4.40	0.104

- Line Observations provide significant improvement
- Both enchancements provide significant improvement
- Some improvement in angular error

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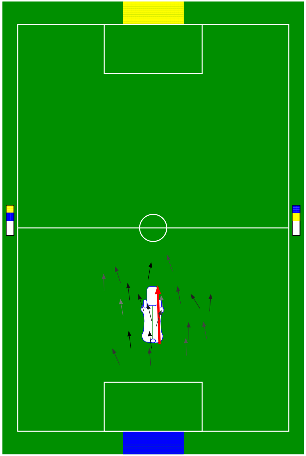
Simulator

- Abstract noisy observations and movements
- Always know ground truth
- Perturbations repeatable
- Misses set fraction of observations



Kidnapped Robot

- Robot follows figure 8 path
  - Kidnapped once every 30 seconds
    - Placed at center of field at random orientation
- Measure position and angle error
  - Averaged over 2 hours (about 50 laps)
- Measure kidnap recovery time
  - Time for the robot to achieve error less than 20 cm and 20 degrees
- Significance results using one-tailed Student's t test

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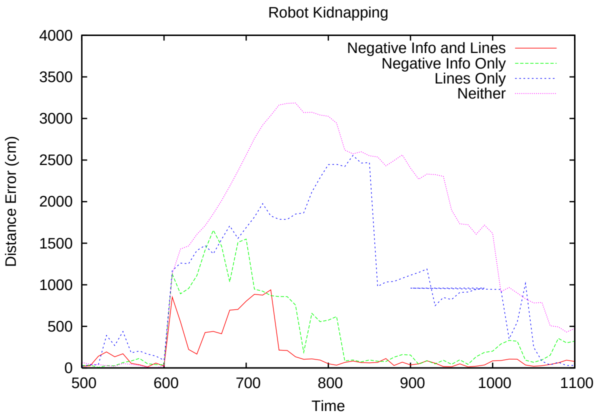
Example Kidnapping



- Kidnapping at time $t = 600$
- Localization Accuracy slowly recovers

Results

Algorithm	Distance Error(cm)	p-value	Angle Error(deg)	p-value	Recovery Time(sec)	p-value
None	46.04	–	15.8	–	7.76	–
NEG	42.29	$< 10^{-6}$	14.0	$< 10^{-7}$	7.53	0.35
LINES	41.19	$< 10^{-8}$	15.3	0.11	6.35	0.01
BOTH	36.74	$< 10^{-29}$	14.2	$< 10^{-5}$	5.86	$< 10^{-3}$

- Algorithm with both enhancements was significantly better than baseline
    - In distance error
    - In angular error
    - In kidnap recovery time
- Algorithm with both enhancements was better than all algorithms in distance error

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Comparison to Hoffmann et al's Method

- Hoffmann et. al's Method
  - Update particles with negative information after one missed observation $t = 1$
- Our method
  - Update particles with negative information after landmark has been missed t times
  - For these experiments, $t = 5$

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Algorithm	Distance Error (cm)	p-value	Angle Error(deg)	p-value
Our Method ($t = 5$)	36.74	–	14.2	–
Hoffmann ($t = 1$)	40.11	$< 10^{-5}$	15.5	$< 10^{-3}$

- Our method performed significantly better
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  - And angular errors

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Related Work

Negative Information

- Hoffmann et al [Robocup 2005, IROS 2005]
  - First implementation of negative information
  - Take occlusions into account
  - Experiments on still robot

Line Observations

- Röfer et al [Robocup 2003, 2005]
  - Discretize field into grids
  - Pre-calculate where line pixels should be in image for each grid cell
  - Update particles based on similarity in line pixel locations

Summary

- Monte Carlo Localization works well
- Want to to make use of all information available
  - Including Negative Information
  - And Line Observations
- Significantly better than baseline approach