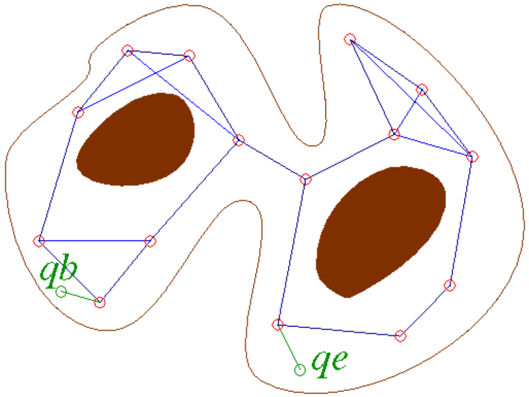
SLAM

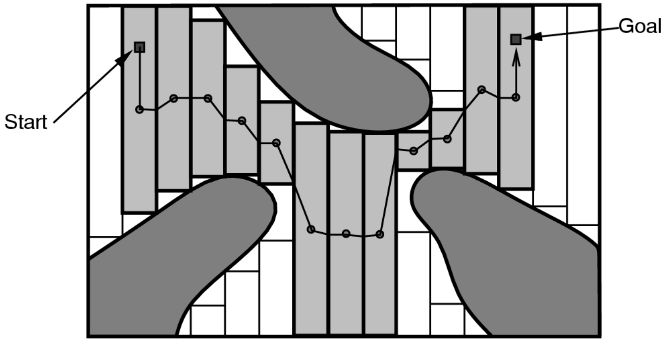
CPSC 470 – Artificial Intelligence
Brian Scassellati

Four Methods for Path Planning in Configuration Space

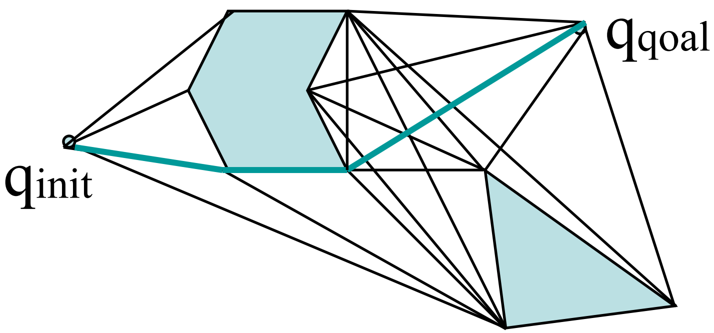
Probabilistic Roadmap



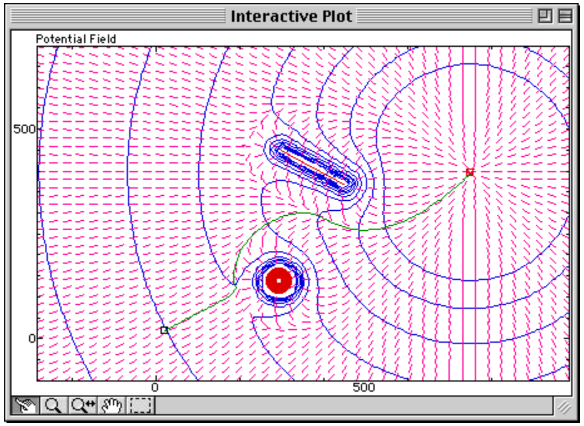
Cell Decomposition



Visibility Graphs



Potential Fields



Potential Field Techniques: A Way to Avoid Planning?

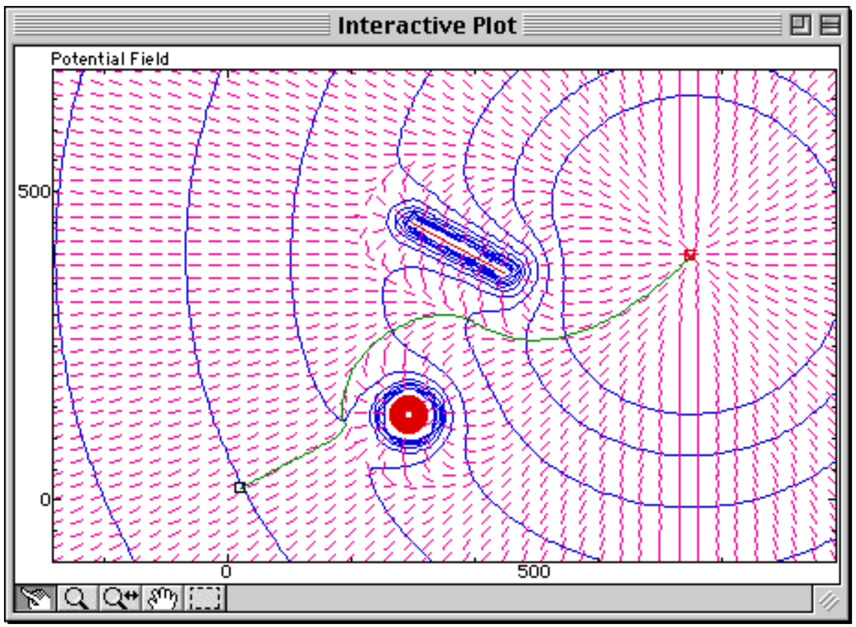


Image from calgera.com

- Potential field: scalar function over the free space
- Ideal field is smooth, with a global minimum at the goal, no local minima, and grows to infinity near obstacles
- Robot moves along with the gradient

Difficulties with Potential Fields

- Computing an ideal potential field is likely to be at least as hard as path planning itself.
- Potential fields are computed by combining forces applied to selected points, called control points, in the robot.
- Such potential fields may have local minima and must be completed by search techniques, e.g., best-first (up to 4 or 5-D configuration spaces) or random (for more dimensions).

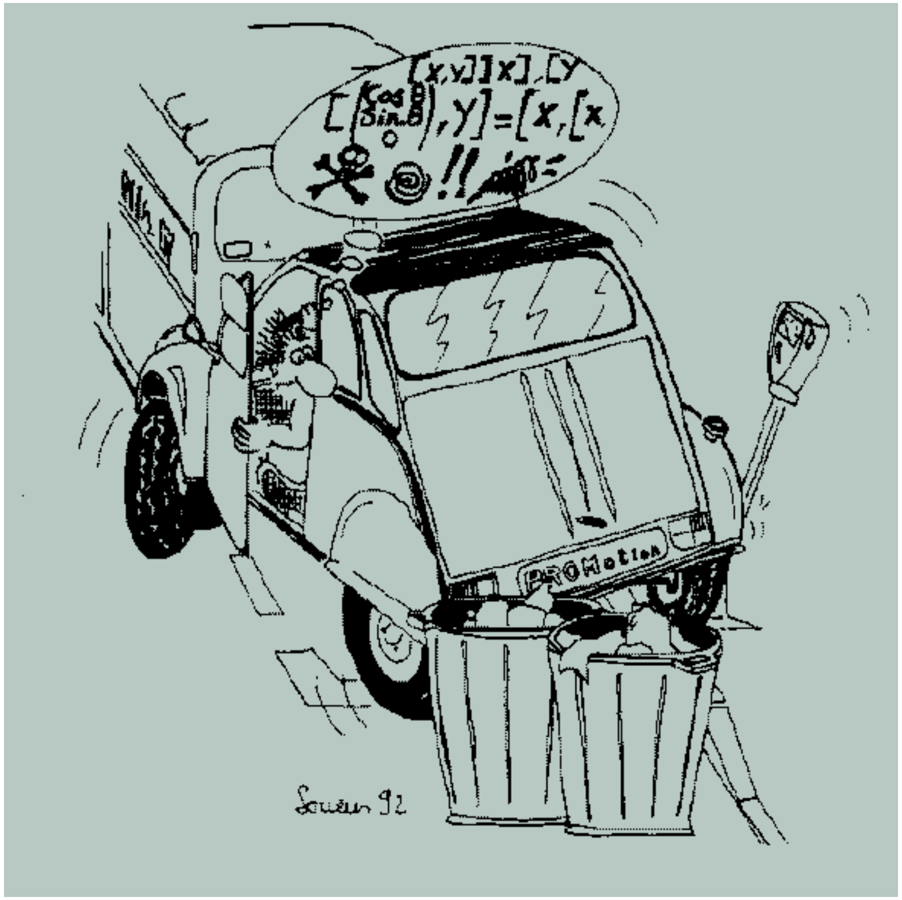
What makes this even harder?

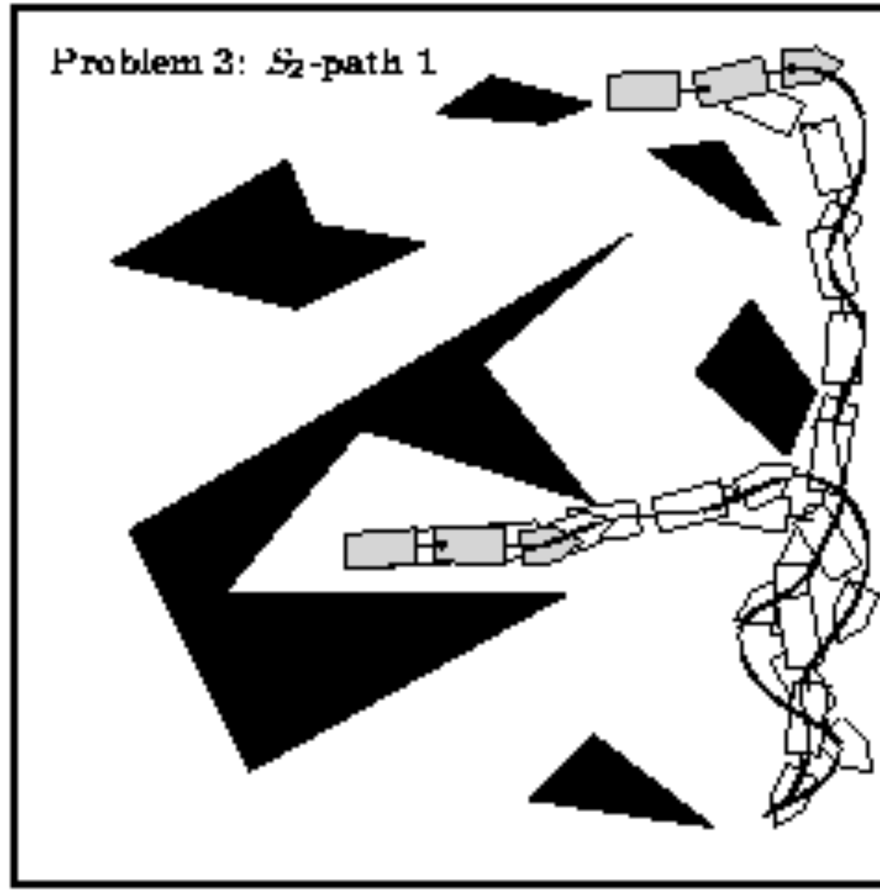
Non-holonomic robots,

Dynamic Environments,

And Uncertainty

Planning for Non-holonomic Robots

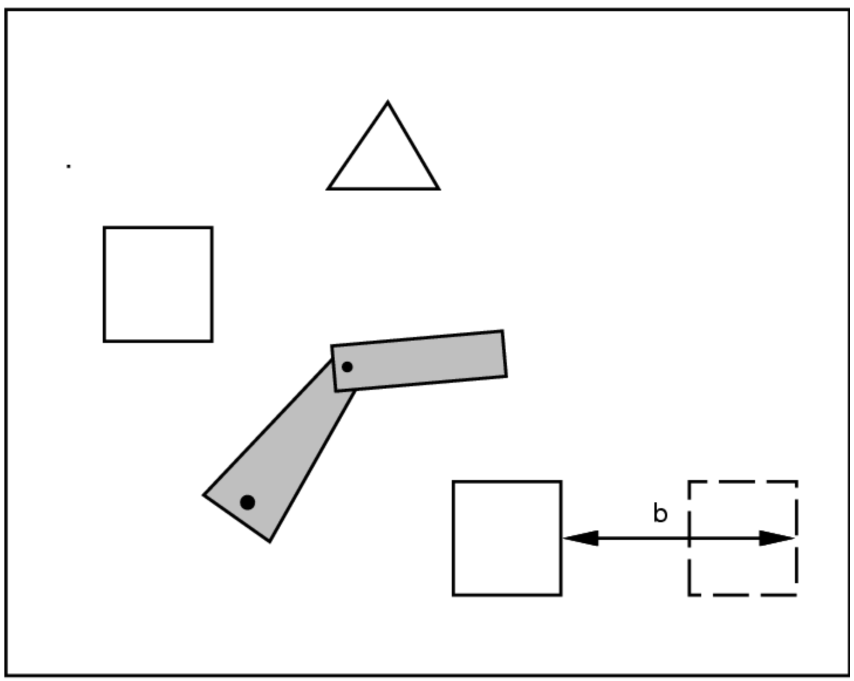




Nonholonomic robots:

Number of controlled DOF does not equal actual DOF

Dynamic Environments



- Impact on configuration space?
  - Increase in the dimensionality
- Solutions:
  - Convert back to a logical planning problem using abstraction
  - Plan object motions, then plan the robot's motion
  - Restrict object motions

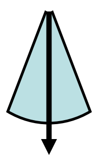
Perfect Knowledge of the World?

- What happens when you don’t know the locations of all the objects?
- What happens when your sensory systems are unreliable?
- What happens when your actuators are unreliable?

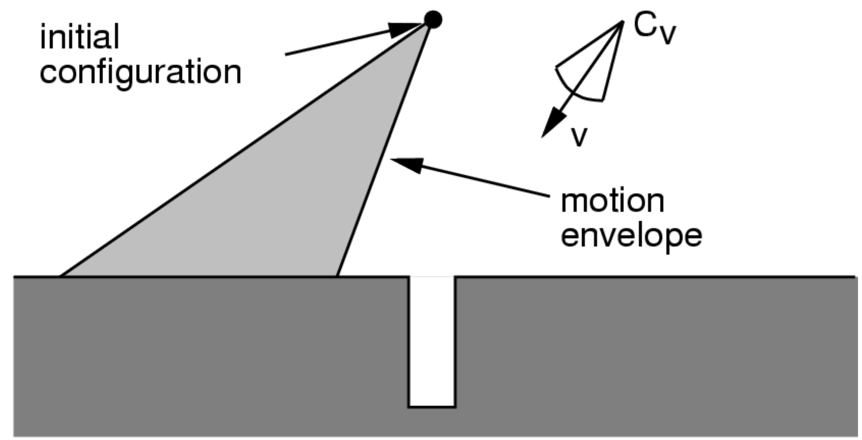
- And many more problems….

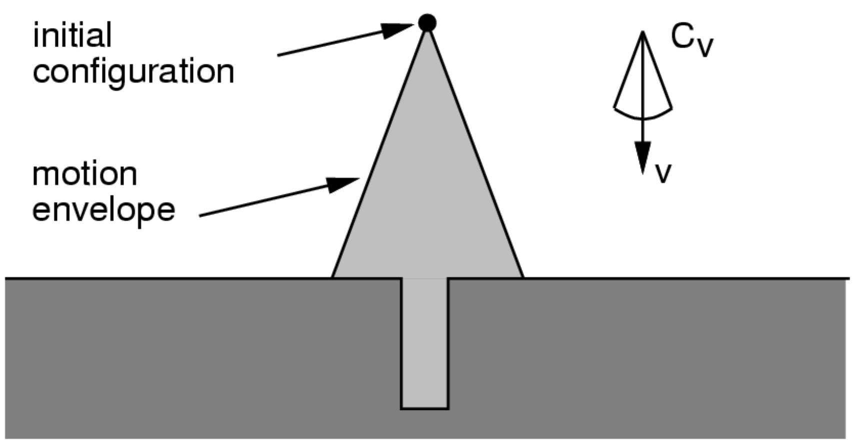
Uncertainty and Motion Planning

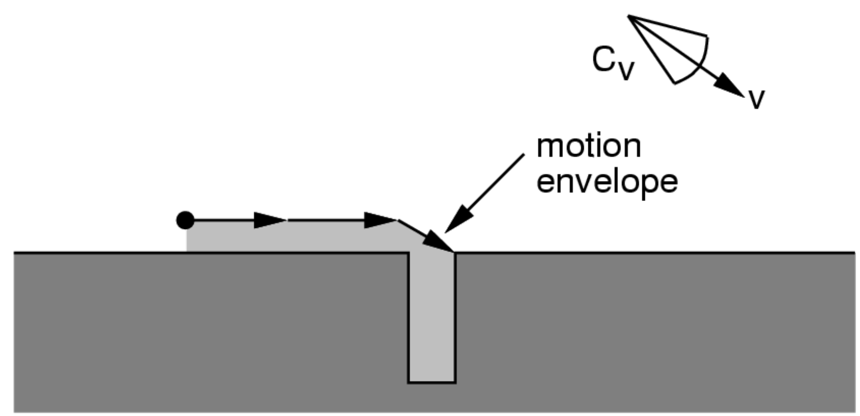
- What if I don't know exactly my position or velocity exactly?



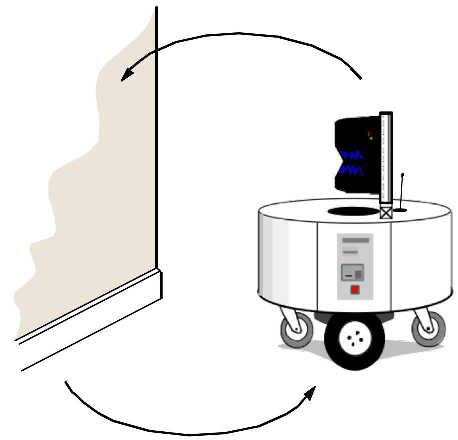
Velocity uncertainty cone





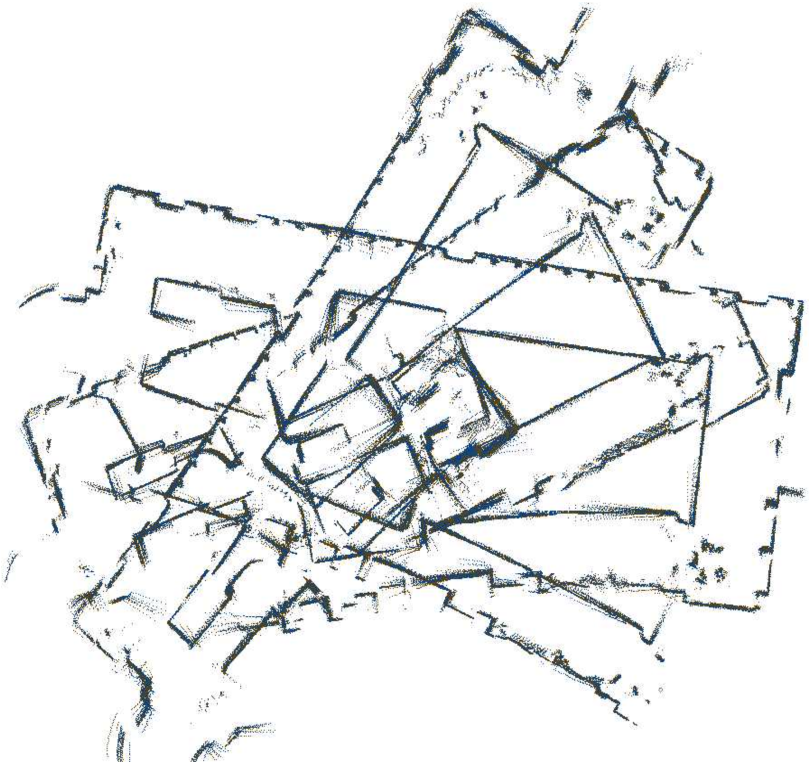


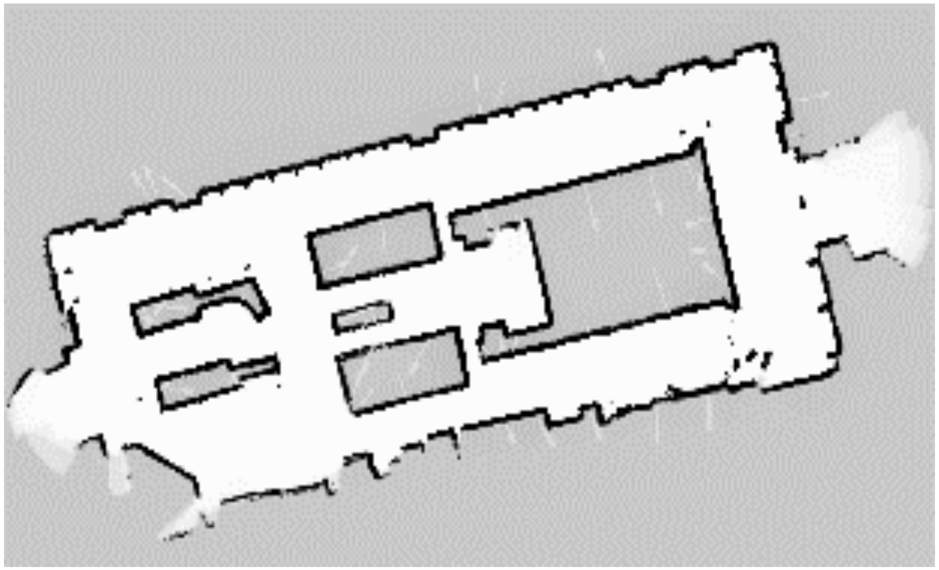
Localization and Mapping



- A Chicken-and-Egg problem
  - Need an accurate map to figure out where we are (localization)
  - Need to know where we are to make a good map (mapping)

Odometry Error and Mapping





- Odometry rarely works
- Small errors in position or map accumulate over time

Navigation Overview

- How can I get there from here?
  - Planning
  - Assumes perfect map, sensing, and actuation
- Where am I?
  - Localization
  - Assumes perfect map, but imperfect sensing
- Exploration (Mapping and Localization)
  - Simultaneous Localization And Mapping (SLAM)

SLAM Problem Statement

- Inputs:
  - No external coordinate reference
  - Time sequence of measurements made as robot moves through an initially unknown environment
- Outputs:
  - A *map* of the environment
  - A robot *pose estimate*

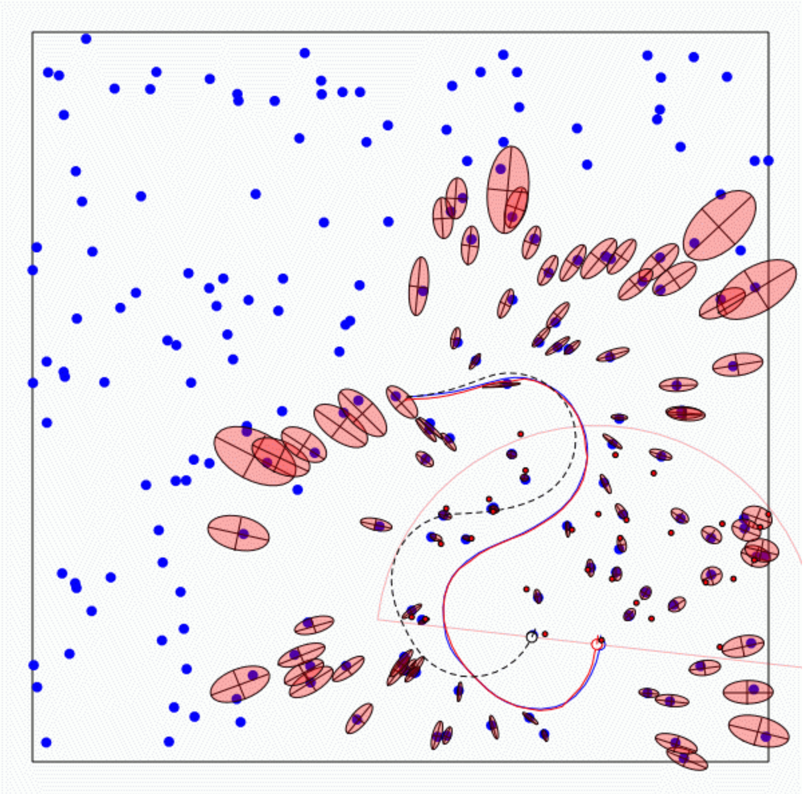
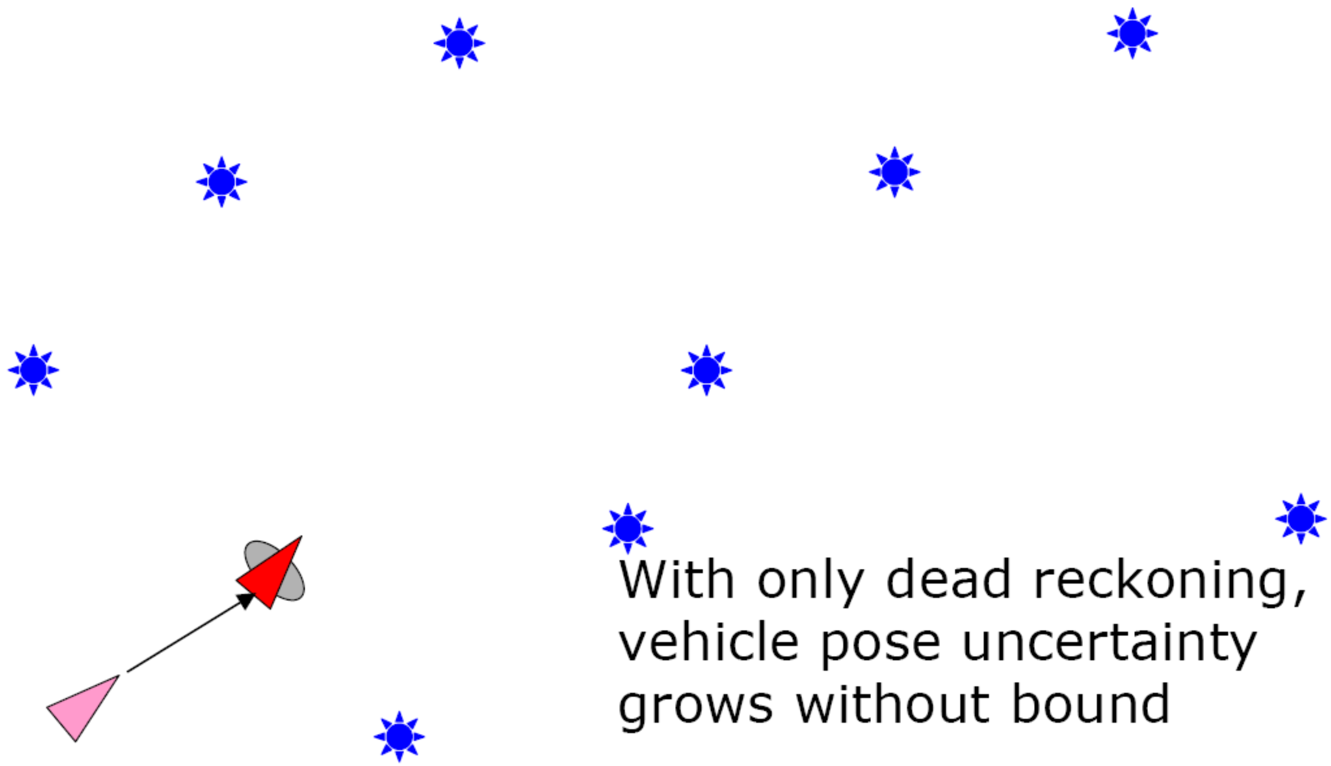
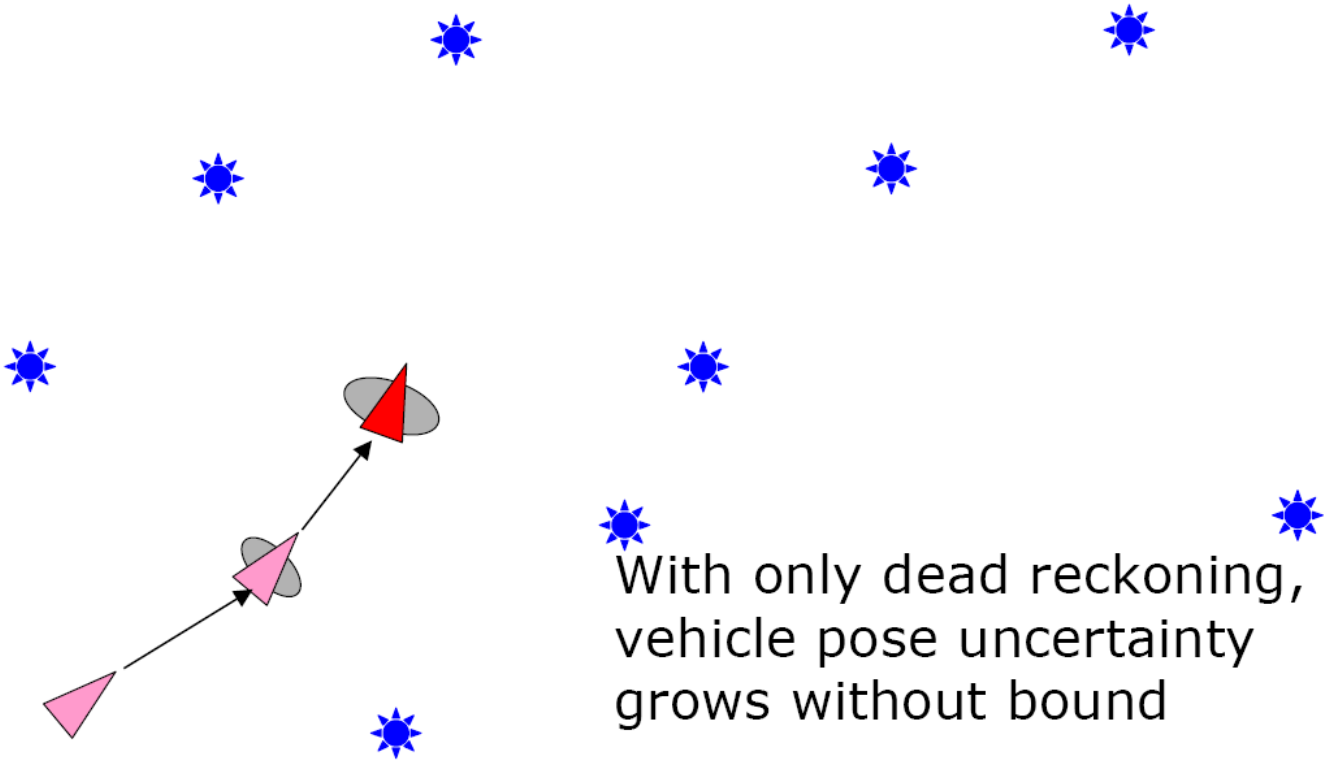


Illustration of SLAM without Landmarks



With only dead reckoning, vehicle pose uncertainty grows without bound

Illustration of SLAM without Landmarks



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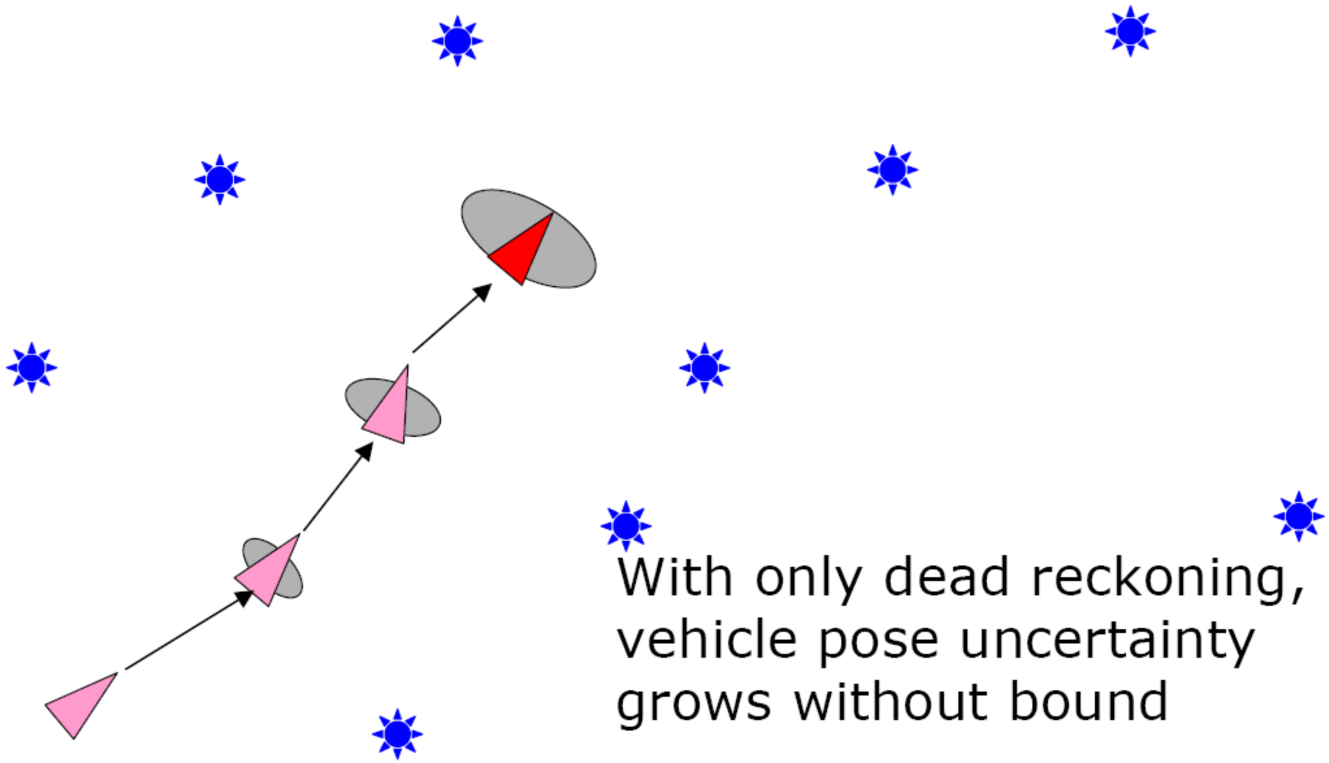

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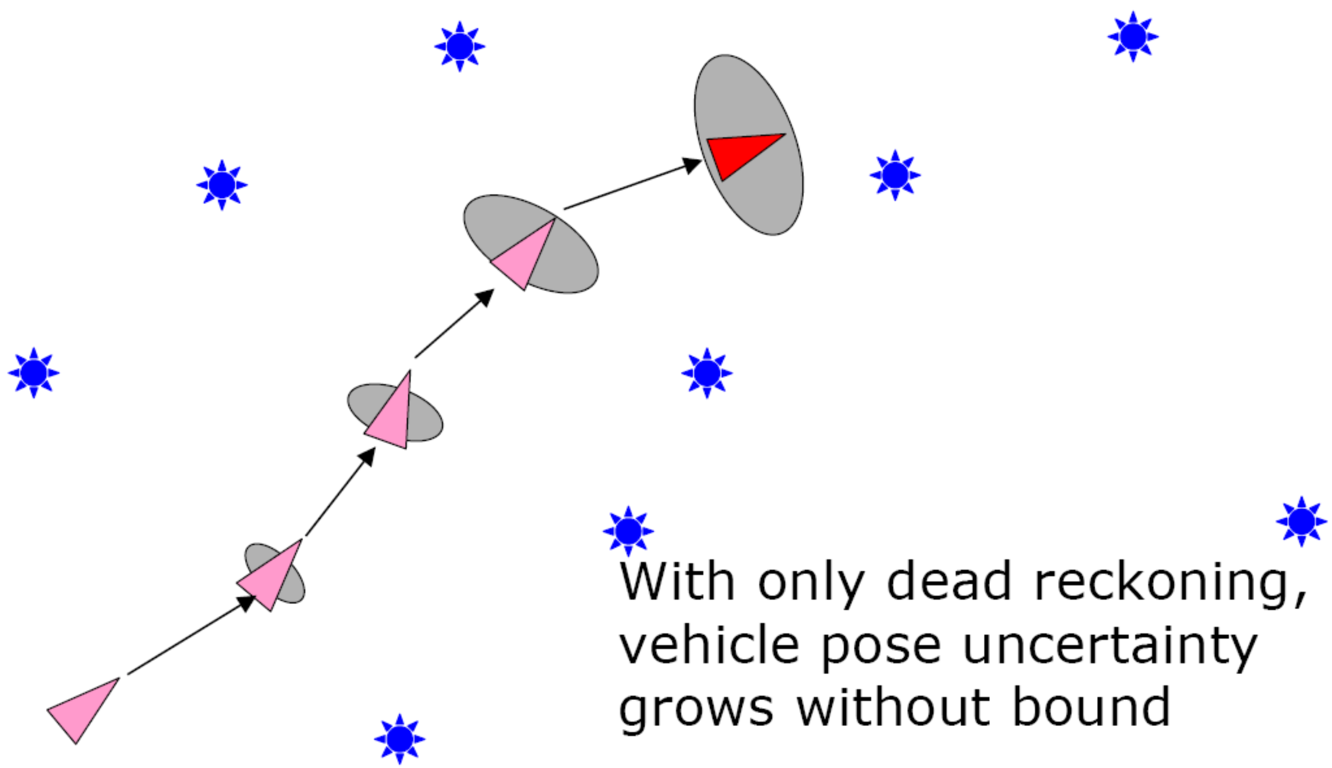

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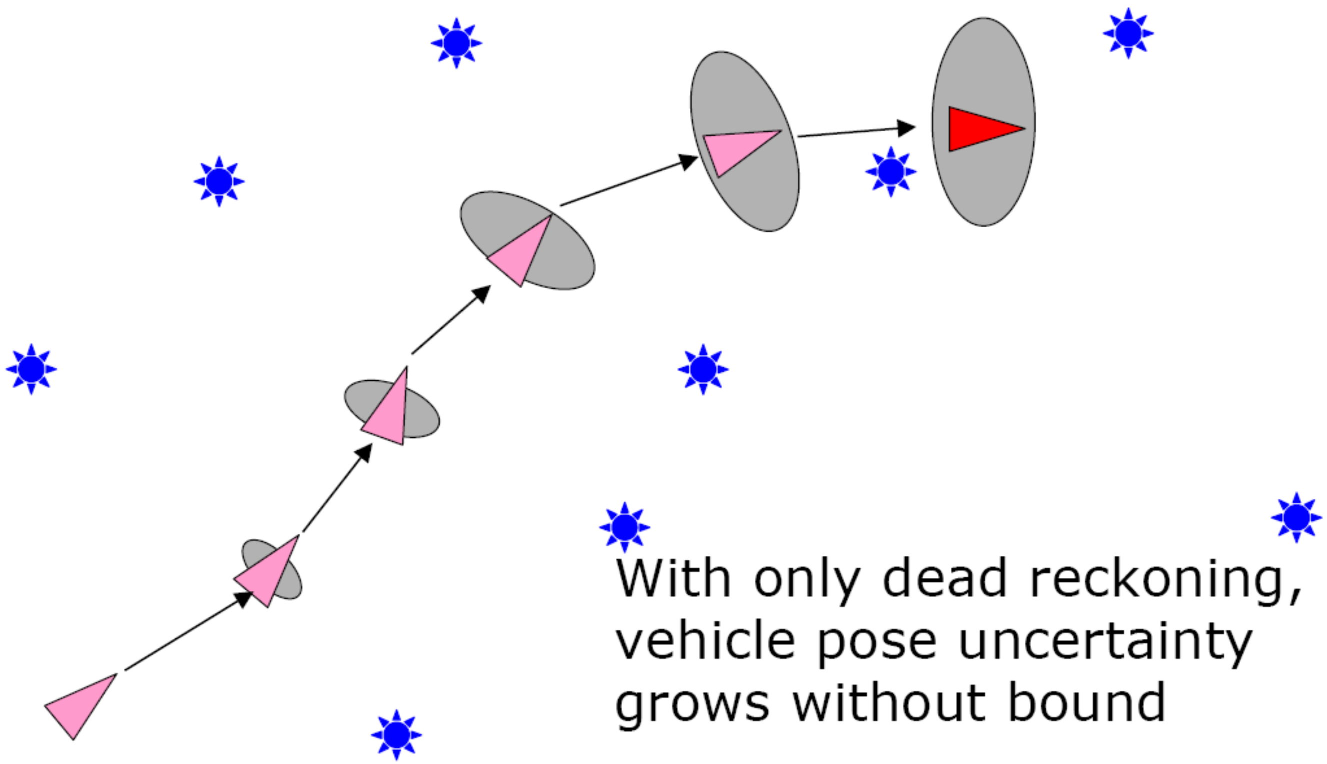
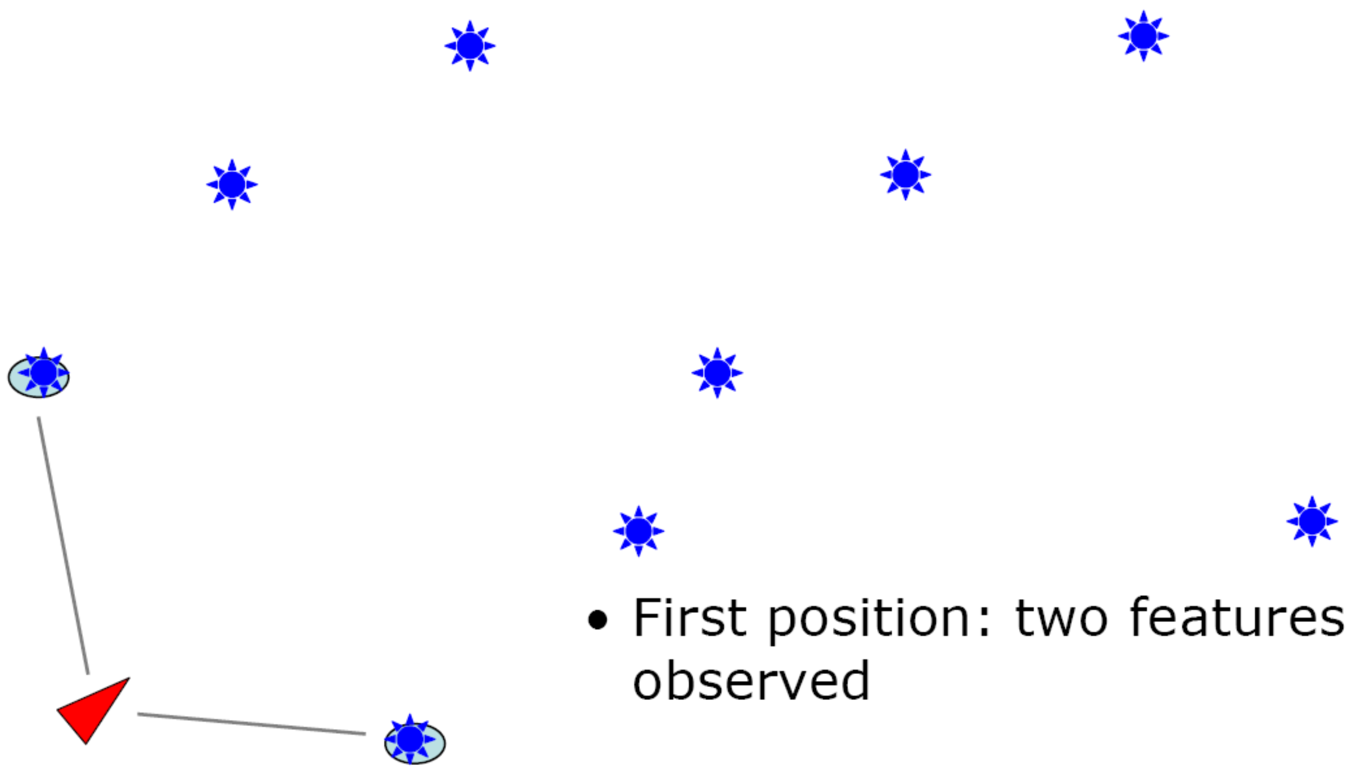


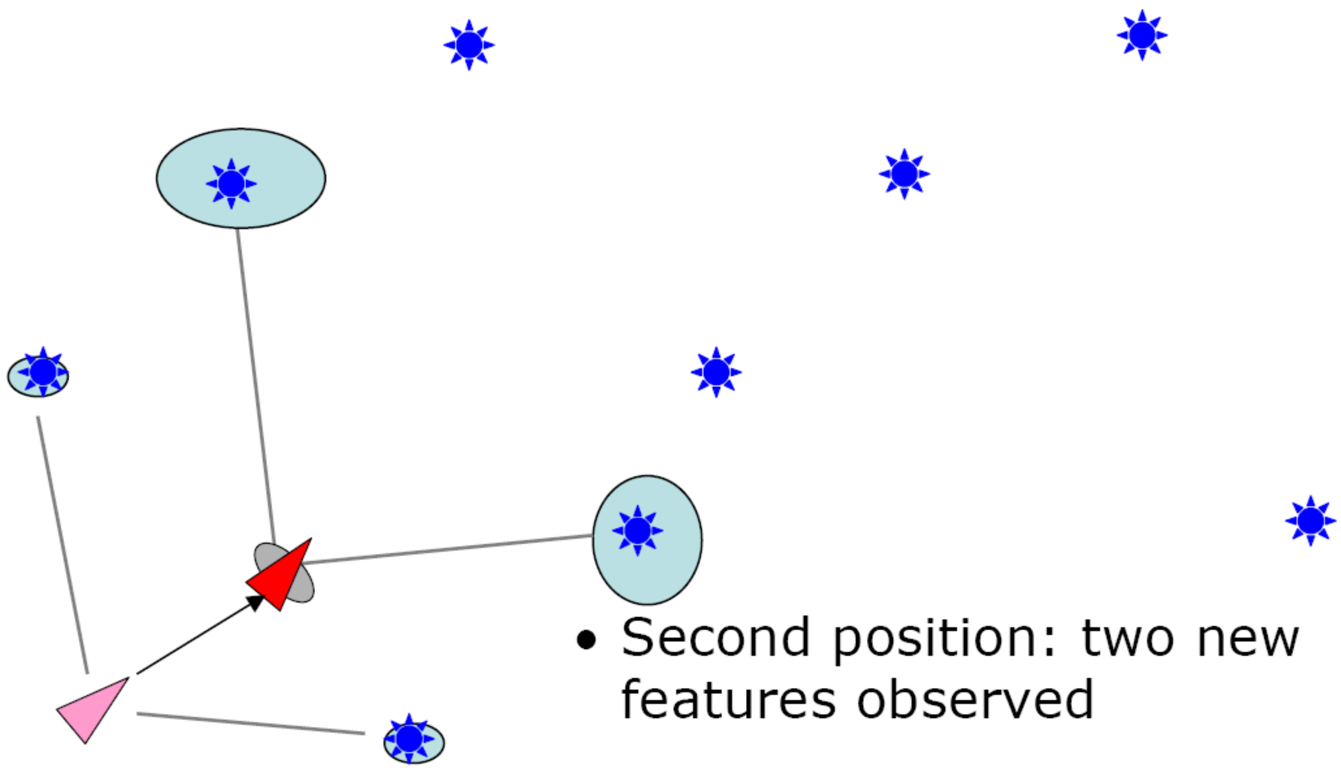
With only dead reckoning, vehicle pose uncertainty grows without bound

Repeat, with Measurements of Landmarks



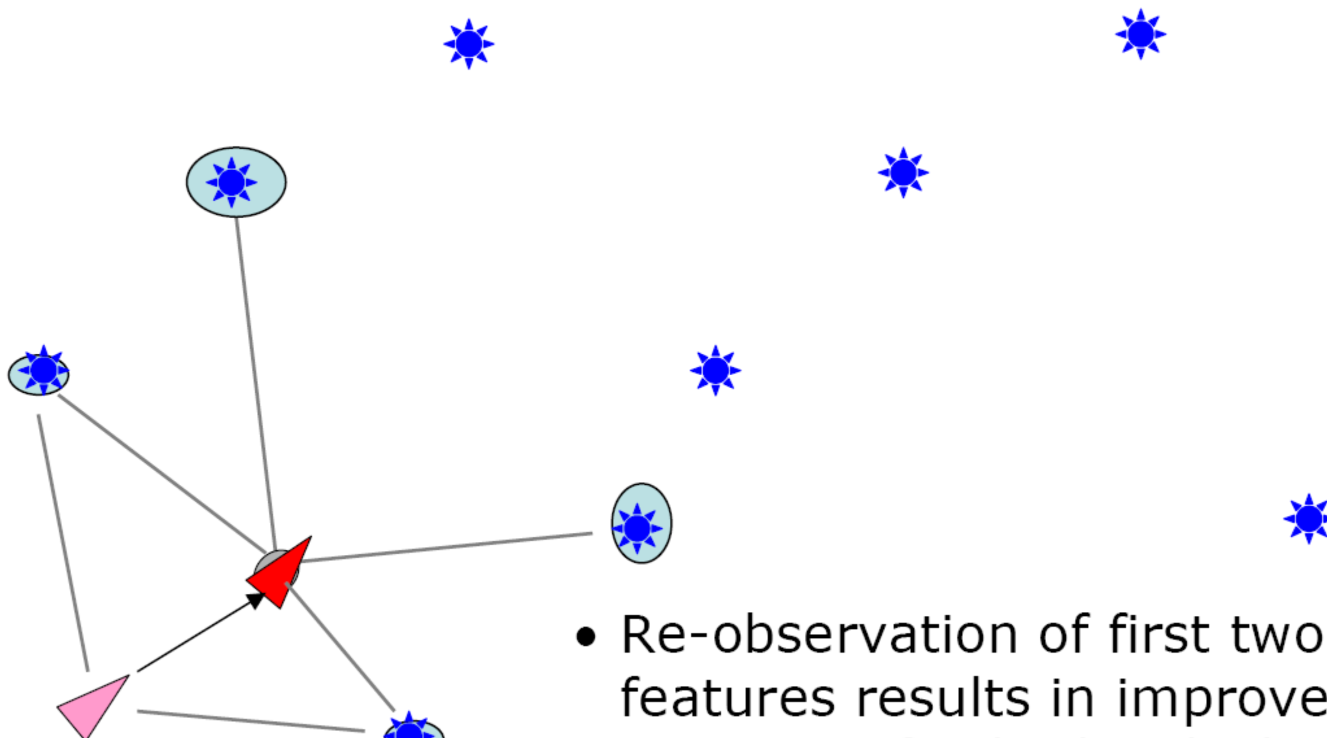
- First position: two features observed

Illustration of SLAM with Landmarks



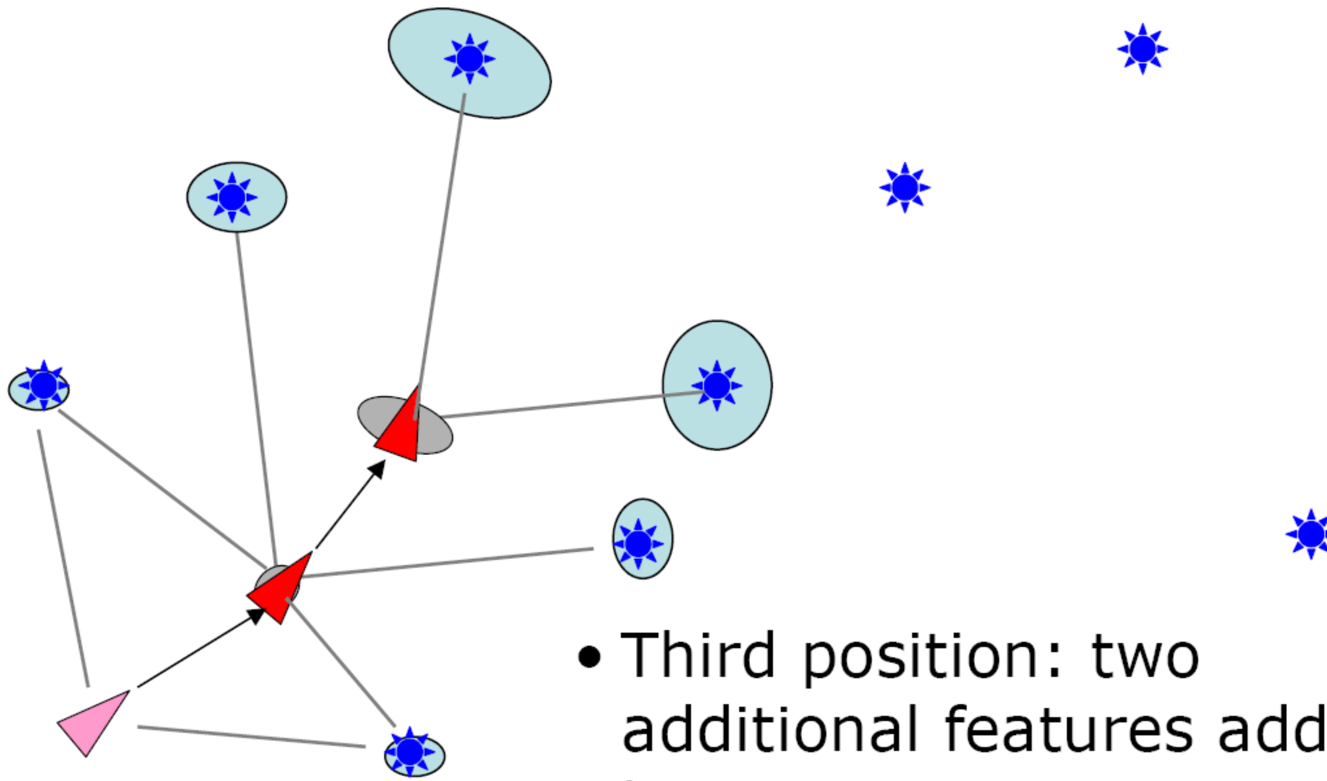
- Second position: two new features observed

Illustration of SLAM with Landmarks



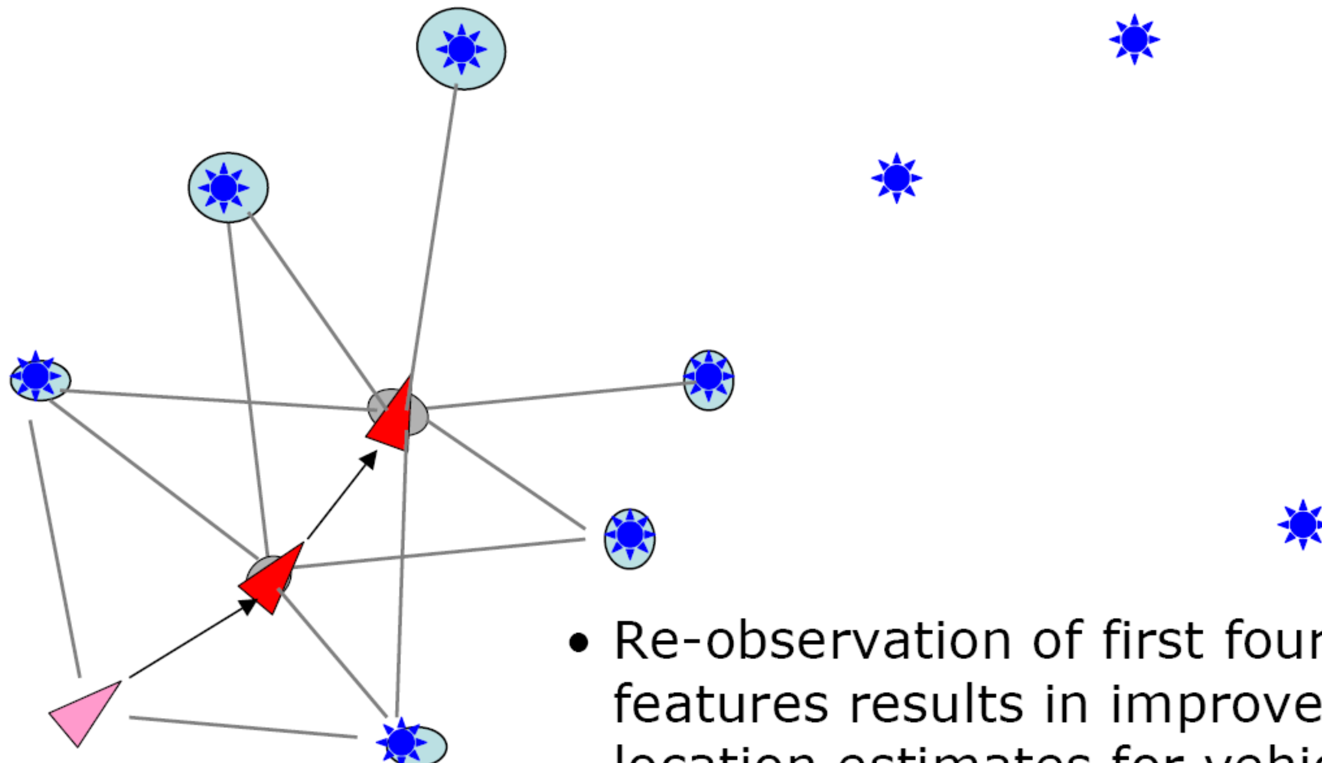
- Re-observation of first two features results in improved estimates for *both* vehicle and feature

Illustration of SLAM with Landmarks



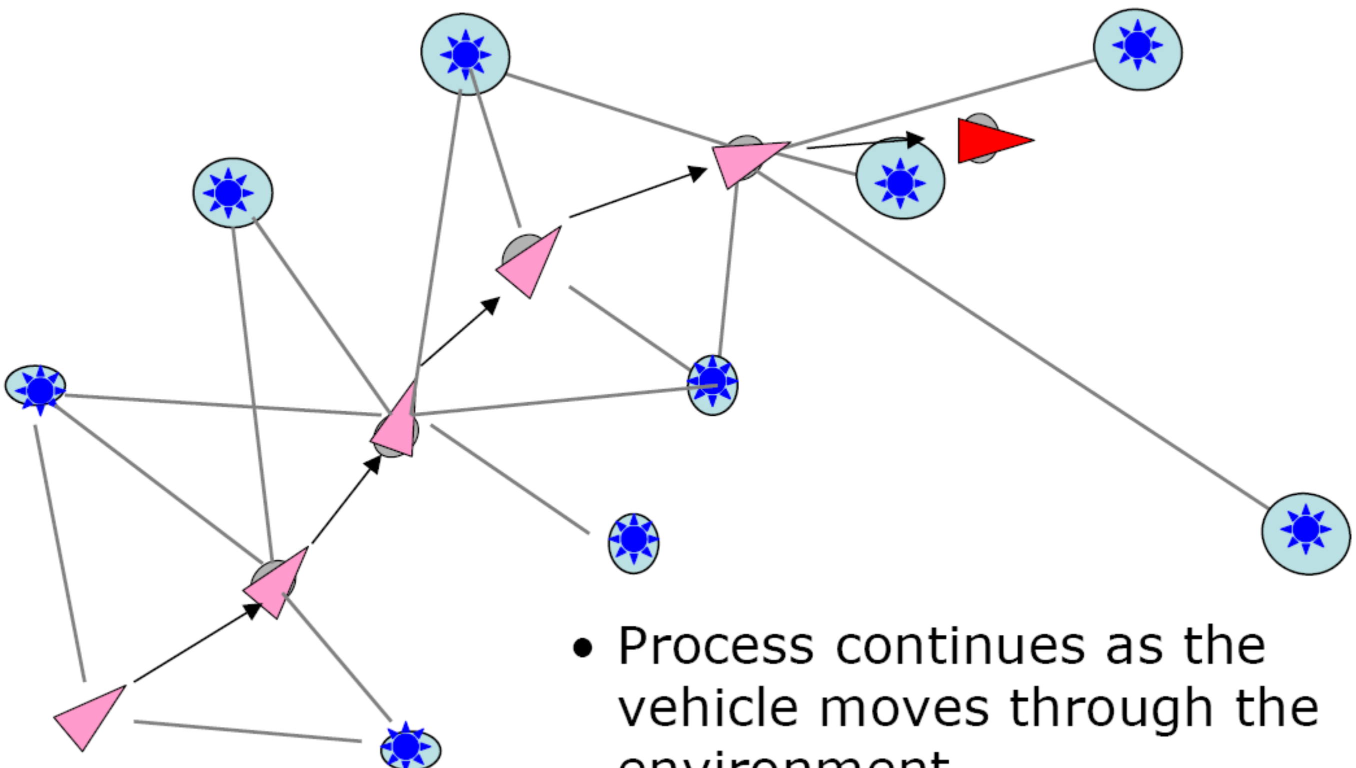
- Third position: two additional features added to map

Illustration of SLAM with Landmarks

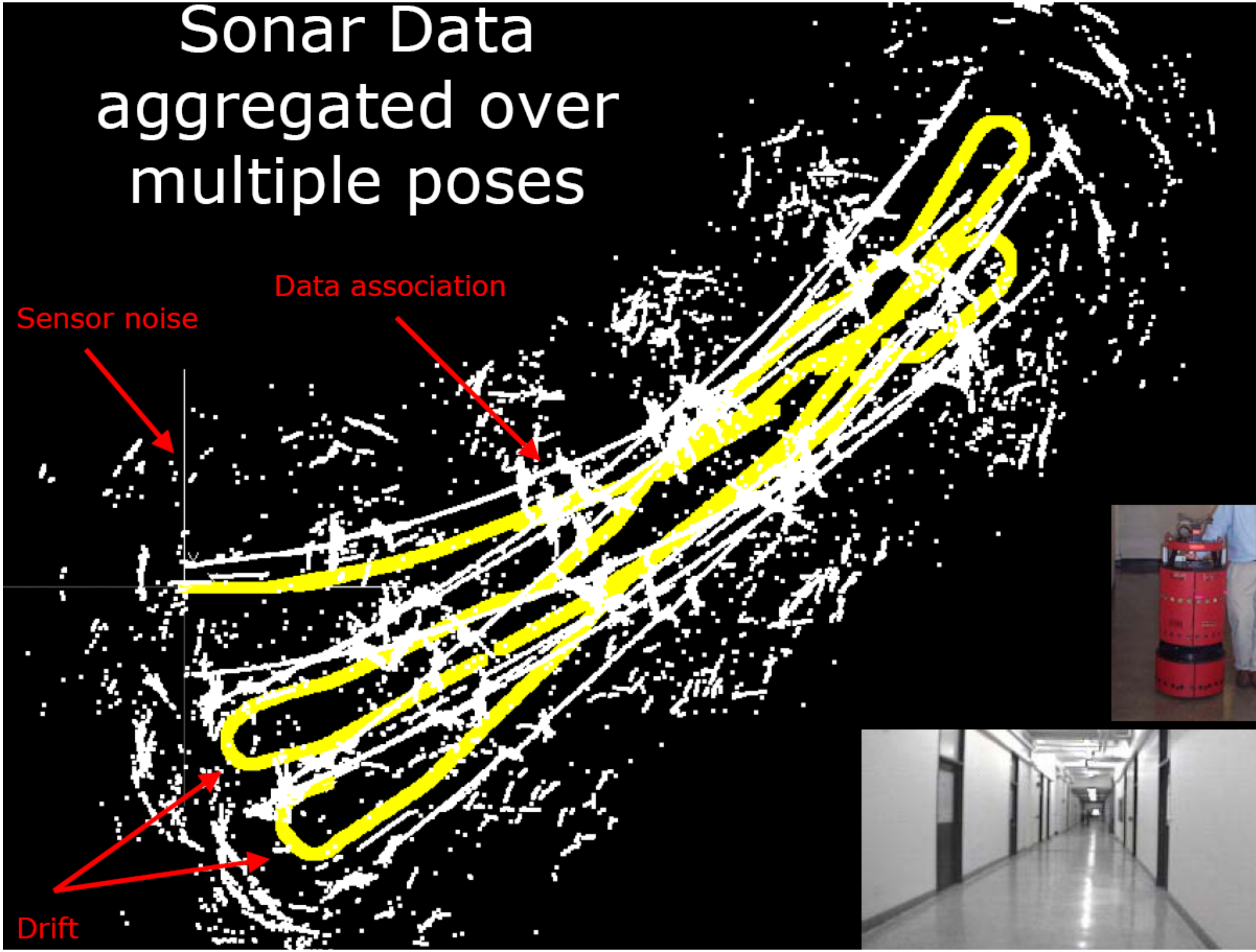


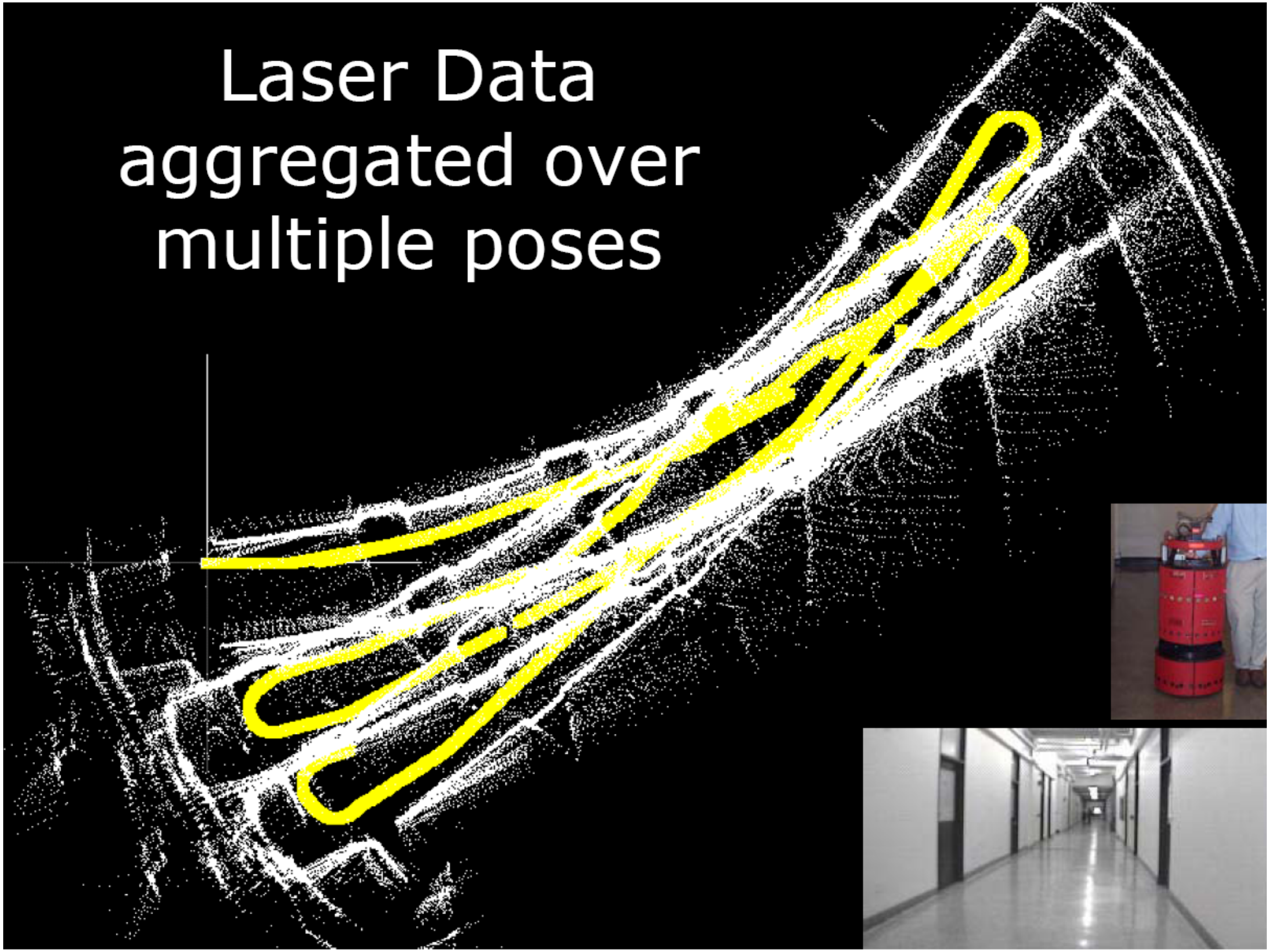
- Re-observation of first four features results in improved location estimates for vehicle and all features

Illustration of SLAM with Landmarks

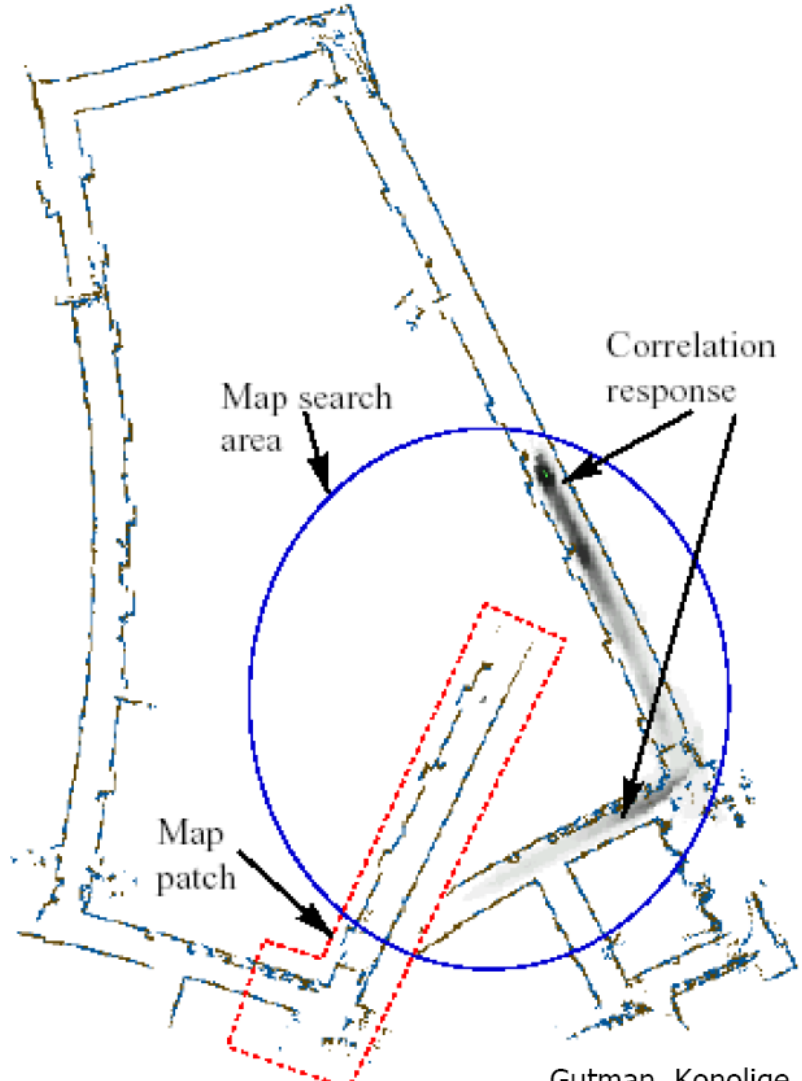


- Process continues as the vehicle moves through the environment


Sonar Data aggregated over multiple poses
Data association
Sensor noise
Drift


Laser Data
aggregated over
multiple poses

Loop Closing



Gutman, Konolige

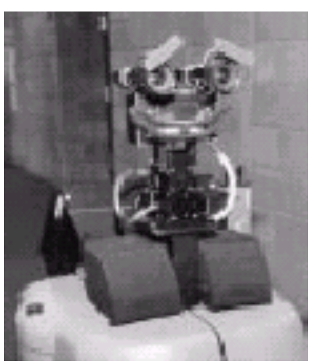
SLAM success stories

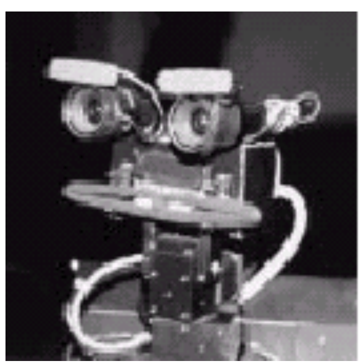
Minerva's Deployment

- Smithsonian Museum of American History
- Two-week period in 1998
  - Total distance traveled: 44 km
  - Maximum speed : 163 cm/s
  - Average speed : 33 cm/s
  - Number of Tours : 630
  - Number of Exhibits : 2,668
  - Total Uptime : 93 hours, 23 minutes
  - Workspace : approximately 67 meters by 53 meters

Minerva's Facial Expressions

- 4 degrees of freedom
  - Mouth corners
  - Eyebrows
- Bar-style LED display behind mouth





(AP PHOTO)

Administrivia

- Coming up:
  - Friday: Robots galore
  - Monday: Healthcare Robotics
  - Wednesday: AI & Ethics
  - Friday: Course summary and AI predictions
- PS 7 due Friday, PS 8 out on Friday (due last day of classes)