CSE-571
AI-based Mobile Robotics

Fast-SLAM Mapping

Many slides courtesy of Wolfram Burgard

Rao-Blackwellized Mapping

Compute a posterior over the map and possible trajectories of the robot :

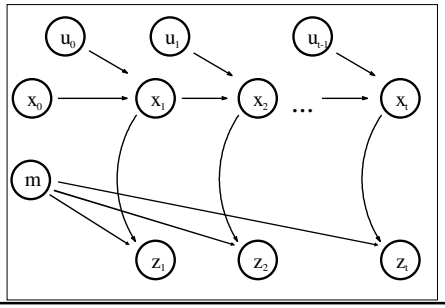
map and trajectory

measurements

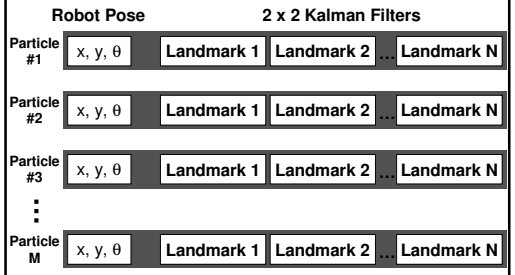
$$p(x_{1:t}, m \mid z_{1:t}, u_{0:t-1}) = p(m \mid x_{1:t}, z_{1:t}, u_{0:t-1})\, p(x_{1:t} \mid z_{1:t}, u_{0:t-1})$$

map robot motion trajectory

A Graphical Model of Rao-Blackwellized Mapping



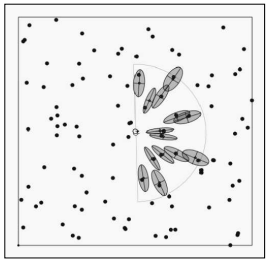
FastSLAM



[Begin courtesy of Mike Montemerlo]

FastSLAM – Simulation

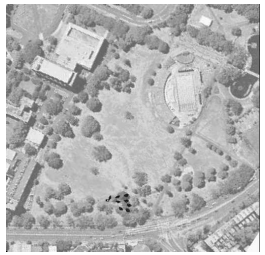
- Up to 100,000 landmarks
- 100 particles
- 10^3 times fewer parameters than EKF SLAM



Blue line = true robot path
Red line = estimated robot path
Black dashed line = odometry

Victoria Park Results

- 4 km traverse
- 100 particles
- Uses negative evidence to remove spurious landmarks



Blue path = odometry
Red path = estimated path

[End courtesy of Mike Montemerlo]

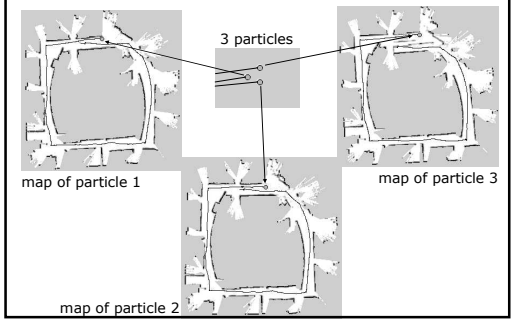
Key Questions

- Can we apply Rao-Blackwellized mapping to large grid-maps?
- How can we compactly represent the individual maps carried by the particles?
- How can we reduce the number of particles needed?

Tasks to be Solved

- Mapping (occupancy grids)
  - Each particle carries its own map m.
  - The history of each particle represents a potential trajectory of the robot.
- Localization
  - Propagate the particles according to the motion model (draw from $p(x|u,x')$).
  - Compute importance weight according to the likelihood of the observation z given the pose x and the map m of the particle.

Example



Map Maintenance Challenges

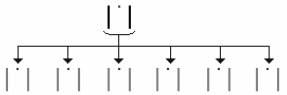
- High resolution maps are big
- Typically 100's or 1000's of particles are needed
- One full map per particle requires
  - O(|m|·n) work (re-sampling)
  - Gigabytes of memory movement
- Anecdotal reports: Tried, but impractical (see later)

Begin courtesy of Eliazar & Parr

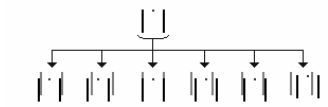
DP-SLAM: Distributed Particle Mapping

- Exploit sampling/re-sampling steps of PF
  - Common ancestry = Redundant map sections
- History representation: Ancestry Tree
  - Leaves correspond to current particles
- New map Representation
  - Store multiple maps in a single grid

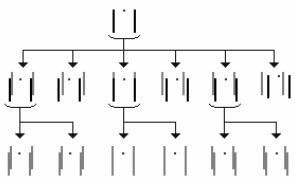
Ancestry Trees



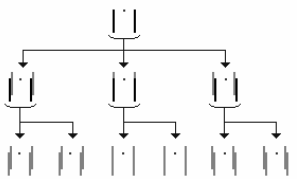
Ancestry Trees



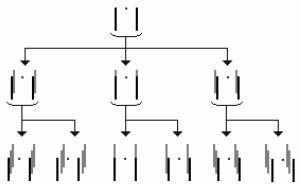
Ancestry Trees



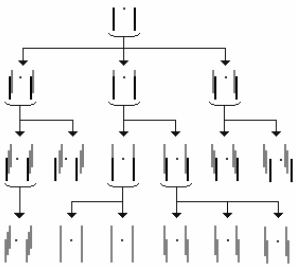
Ancestry Trees



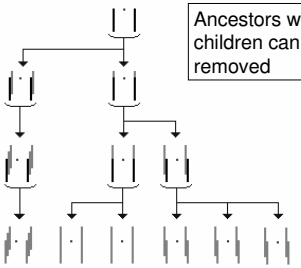
Ancestry Trees



Ancestry Trees

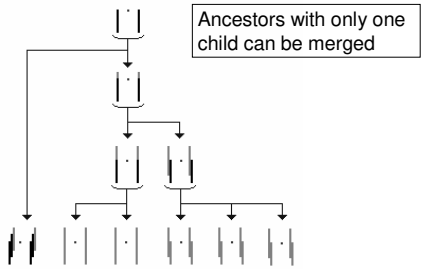


Ancestry Trees

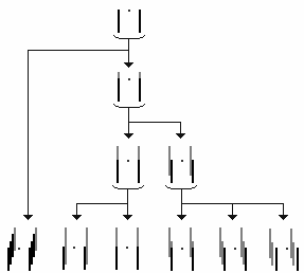


Ancestors with no children can be removed

Ancestry Trees



Ancestry Trees

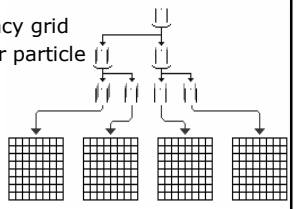


Ancestry Trees

- Maintain a minimal tree (improves complexity)
  - Exactly n leaves
  - Branching factor at least 2
  - Depth no more than n
- Explicitly store the ancestry info
  - Node = Ancestor particle with unique ID
  - Stores parent link, map updates

Map Representation

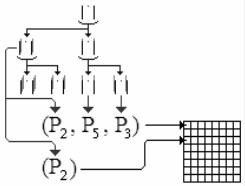
- Map is an occupancy grid
- Avoid one map per particle



Naïve Map Representation

DP-Mapping

- Distribute particles over a single map
- Each grid square stores:
  - ID of each ancestry node that has seen this square
  - Associated observations
  - No redundant data
  - No unnecessary data



Localization

- For each laser cast of the current particle
  - Trace laser cast through grid
  - For each grid square return map occupancy
- Store observations as balanced trees (keyed on IDs)
  - Linear storage ancestry
  - Logarithmic access/updates

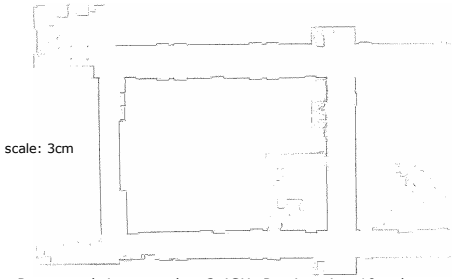
Complexity Summary

- Total Time : $O(An^2)$
  - Compare to $O(|m|n)$
  - $|m| >> An$

A	=	Area observed
n	=	Number of particles
$\|m\|$	=	Map size

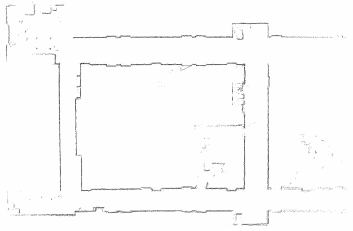
- Linear in observation size
- Independent of map size

DP-SLAM Results

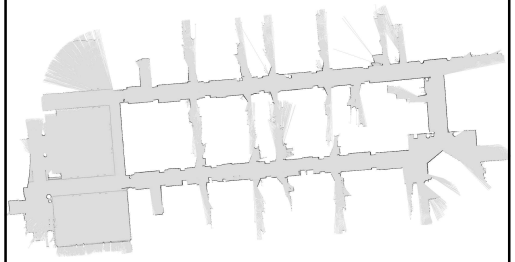


Run at real-time speed on 2.4GHz Pentium 4 at 10cm/s

Consistency

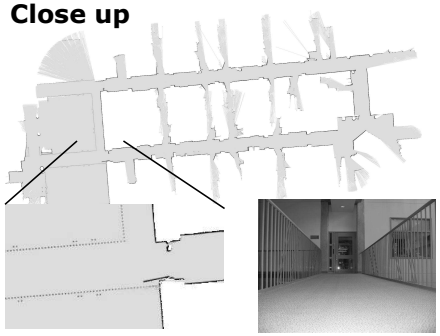


Results obtained with DP-SLAM 2.0 (offline)



Eliazar & Parr, 04

Close up



End courtesy of Eliazar & Parr

Observations

- DP-SLAM is an efficient and elegant way to store the individual maps assigned to the particles.
- Complexity $O(An^2)$ where n is the number of particles
- How can we reduce the number of particles?

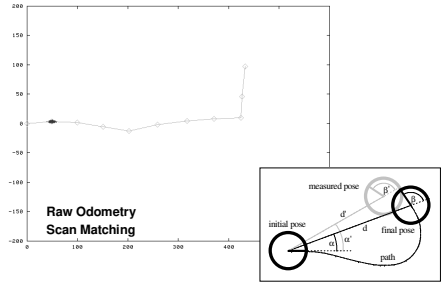
Techniques to Reduce the Number of Particles Needed

- Better proposals (put the particles in the right place in the prediction step).
- Avoid particle depletion (re-sample only when needed).

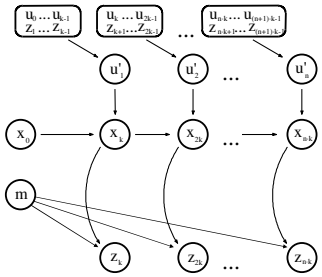
Generating better Proposals

- Use scan-matching to compute highly accurate odometry measurements from consecutive range scans.
- Use the improved odometry in the prediction step to get highly accurate proposal distributions.

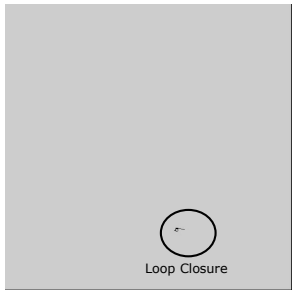
Motion Model for Scan Matching



Graphical Model for Mapping with Improved Odometry

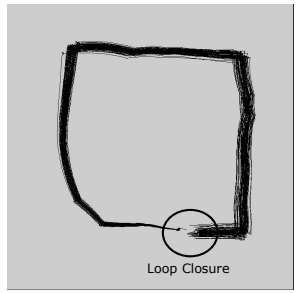


Rao-Blackwellized Mapping with Scan-Matching



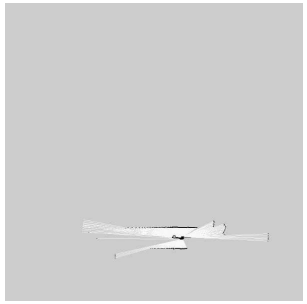
Map: Intel Research Lab Seattle

Rao-Blackwellized Mapping with Scan-Matching



Map: Intel Research Lab Seattle

Rao-Blackwellized Mapping with Scan-Matching



Map: Intel Research Lab Seattle

Example (Intel Lab)

- **15 particles**
- four times faster than real-time P4, 2.8GHz
- 5cm resolution during scan matching
- 1cm resolution in final map

joint work with Giorgio Grisetti

Outdoor Campus Map

- **30 particles**
- 250x250m^2
- 1.088 miles (odometry)
- 20cm resolution during scan matching
- 30cm resolution in final map

joint work with Giorgio Grisetti

Fast-SLAM Summary

- Full and online version of SLAM
- Factorizes posterior into robot trajectories (particles) and map (EKFs).
- Landmark locations are independent!
- More efficient proposal distribution through Kalman filter prediction
- Data association per particle