DP-SLAM

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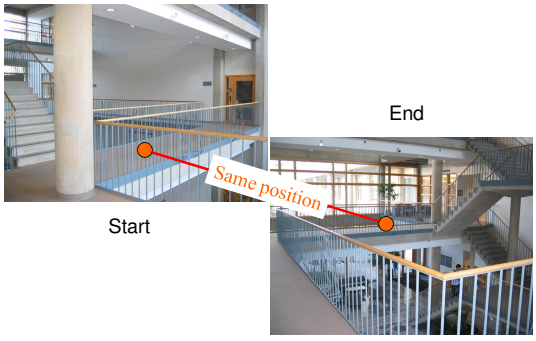
Contains Joint work with Austin Eliazar

Why is SLAM Hard: Ambiguity



Where This is Going

- New DP-SLAM 2.0 algorithm
  - Fast maintenance of multiple map hypotheses
  - Linear run time in all relevant parameters
- New model of laser penetration
- Results:
  - Good asymptotics (mapping no more expensive than localization!)
  - *Very* accurate & detailed maps

Outline

- Digression: Tracking
- Kalman Filter SLAM
- Full map slam
- DP-SLAM

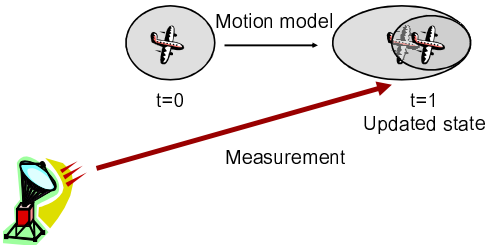
Tracking

- Example: Radar
- Hidden state variable(s)
- Dynamic model
- Noisy observations
- Problem: Infer hidden variables

Tracking Algorithm Outline

- Inputs:
  - Initial state estimate
  - Motion model, observation model
- Main loop:
  - Project state estimate forward using motion model
  - Make observations
  - Update state estimate based on observations

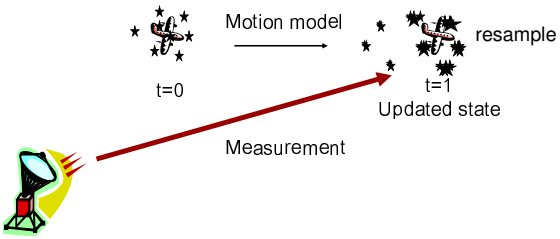
Tracking Example



State Representation

- Assuming:
  - Gaussian initial state
  - Linear dynamics
  - Linear observation model
  - Gaussian noise
- Posterior remains Gaussian
- Closed form solution – Kalman Filter
- See page by Greg Welch and Gary Bishop

Monte Carlo Approximation (Particle Filter)



Particle Filter

- No assumptions about
  - Motion, observation model
  - Form of density
- Simulate → Weight → Resample
- Samples (particles) are fixed in number
- Nota bene: Resampling allocates particles to highest probability areas
- Works well w/concentrated posterior

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SLAM as Tracking

- Hidden state:
  - Robot position
  - Position of distinctive landmarks
- Motion model:
  - Robot control input
  - Landmarks are stationary
- Observations:
  - Measured distances from landmarks

SLAM Pseudocode

Localization

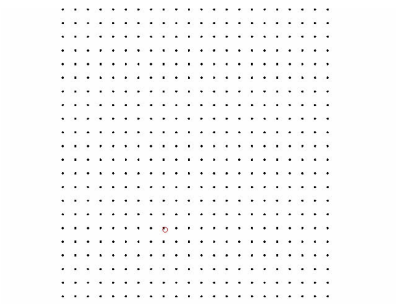
- Project robot state distribution forward (robot motion model)
- Observe environment (laser scans)
- Update robot state by P(O|S)
- Update map (add new objects)
- Repeat

Laser cast tracing
Laser error model

Kalman Filter SLAM Properties

- Assumes:
  - Linear motion model
  - Gaussian noise
- Produces
  - Robot position estimates
  - Landmark position estimates
  - Means and full covariance matrix

KF SLAM Example



Video courtesy of Mark Paskin

Problems with KF SLAM

- Reality is not linear Gaussian
- Produces only a map of landmarks
- n landmarks: $O(n^2)$ cost
- Data association problem

Fixes for KF SLAM

- Thin junction tree filters (Paskin)
  - Uses approximate Bayes net inference techniques
  - Fast, adaptive approximation
- FastSLAM (Montemerlo et al.)
  - Samples robot positions
  - KF for landmark positions
  - Benefits of sampling:
    - Fixes unrealistic linear-Gaussian assumption
    - Landmark positions become independent
    - Linear cost in no. of landmarks seen

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Building a Dense Map

Challenges of Full Maps

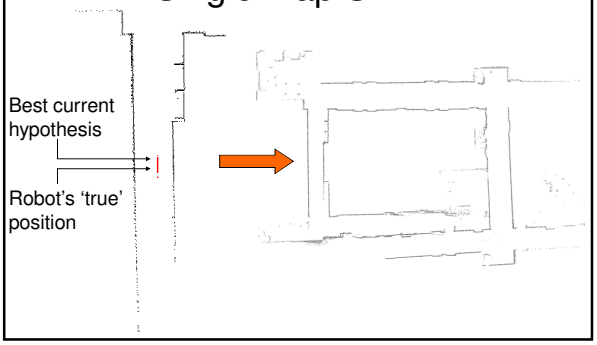
- Dense concentration of features
  - Makes KF impractical
  - Complicates data association
- Naïve approaches fail
  - Ignoring uncertainty = accumulating error in maps
  - Confronting uncertainty = computational problems

(solved by DP-SLAM)

Ignoring Uncertainty

- Use a very accurate sensor (laser)
- Maintain PF or KF over robot positions
- Deterministically update map
  - Estimate most likely robot position
  - Insert new observations into map
  - Hope for the best…

Single Map SLAM



Map Patching

- Exploit topology for consistent maps
  - Loop closing [Lu & Milios '97; Gutmann & Konolige '00]
  - Consistency provides accuracy
- Heuristic map correction
- Good maps achieved at intervals
  - Intermediate maps can be poor
  - Removes *Simultaneous* from SLAM

Outline

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DP-SLAM Goals

- Best of both worlds
  - Soundness/robustness of probabilistic methods
  - Full map detail
- Speed/Efficiency
  - Linear in observation size
  - Linear in number of particles
  - Single pass over sensor data (no map patching required)
- Generality
  - No assumptions about the environment
- Accuracy
  - Full maps without accumulating error

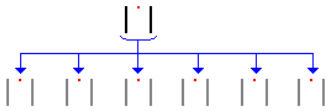
Map Maintenance Challenges

- Want to filter entire, joint pose-map states
- Dense maps are *big*
- 100's or 1000's of particles are needed
- One full map per particle requires
  - O(MP) work (resampling)
  - Gigabytes of memory movement
- Anecdotal reports: Tried, but impractical

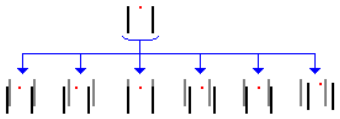
Distributed Particle Mapping

- Exploit sampling/resampling 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

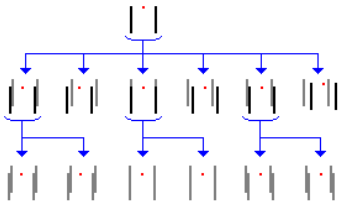
Ancestry Trees



Ancestry Trees



Ancestry Trees



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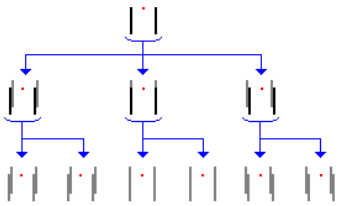

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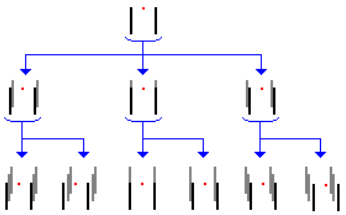
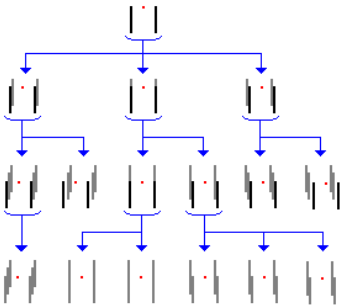
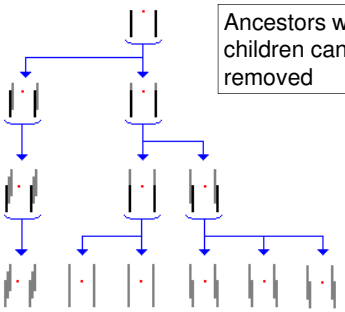


Ancestry Trees



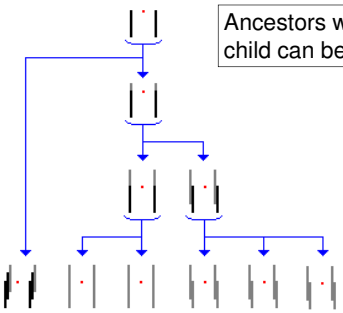
Ancestry Trees

Ancestors with no children can be removed

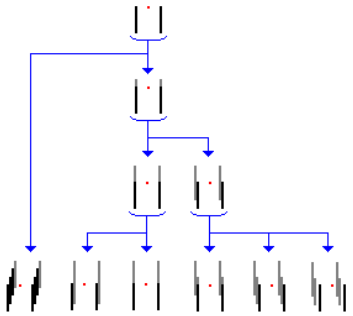


Ancestry Trees

Ancestors with only one child can be merged



Ancestry Trees

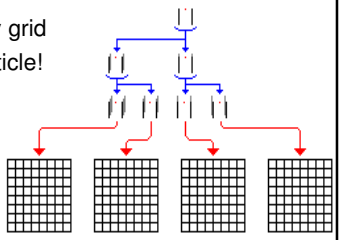


Ancestry Trees

- Maintain a minimal tree (improves complexity)
  - Exactly **P** leaves
  - Branching factor at least 2
  - Depth no more than **P**
- Explicitly store the ancestry info
  - Node = Ancestor particle w/ unique ID
  - Stores parent link, grid squares updated (list)

Naïve Map Representation

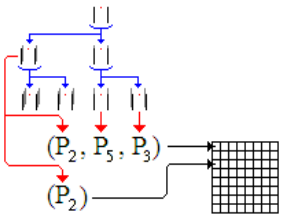
- Map is an occupancy grid
- One full map per particle!



Naïve Map Representation

DP-Mapping

- Each ancestry node stores
  - "Vector" of updated grid squares
- Each grid square stores:
  - "Vector" of ancestry nodes that have updated the square
  - Associated observations
- Good News:
  Minimal redundancy
- Bad News: Sacrifices constant time access to map



SLAM Pseudocode

Localization

- Project robot state distribution forward (robot motion model)
- Observe environment (laser scans)
- Update robot state by P(O|S)
- Update map (add new objects)
- Repeat

Laser cast tracing
Laser error model

Localization Complexity

- P Particles
- Must compute P(O|S) for each particle
- For each laser cast of the current particle
  - Trace laser cast through grid
  - For each grid square return map occupancy
  - Laser scan probability = f(map occupancy)
  - Trivial for explicit map representation
  - Observation size A: O(AP)

DP-SLAM Localization

- For DP Maps
  - Must implicitly reconstruct each particle's map
  - For each ancestor of current particle:
    - Check if this node has updated current square
    - Return associated occupancy
- Naïve Solution:
  - For each P on frontier of ancestry tree: O(P)
  - For each square A visited tracing laser casts: O(A)
  - For each node D in ancestry tree on path from P to root: O(P)
  - Check if node D has updated A: O(P)
- $O(AP^3)$ complexity

A Smarter Solution

- Assign particles sequential IDs
- Store observation vectors for each grid square as a balanced tree keyed on IDs
- Working smarter:
  - For each P on frontier of ancestry tree: O(P)
  - For each square A visited tracing laser casts: O(A)
  - Simultaneously traverse: } O(P)
    - Ancestry from P to root
    - Balanced tree of observations for P
- $O(AP^2)$ complexity

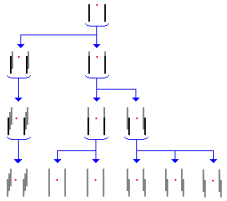
A Linear Solution

- For any iteration of the particle filter:
- On the first visit to any grid square A: O(A)
  - Parse *all* current particles against observation data stored at A: O(P)
  - Cache result } O(AP)
- On subsequent visits to A: O(AP)
  - Return cached result: O(1) } O(AP)
- O(AP) + O(AP) = O(AP) complexity

Alternate view will be presented later!

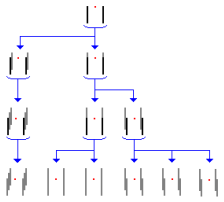
Map Update Complexity

- Updates trickier than they seem at first
- Expensive part: Collapsing
- Q: How to bound collapsing cost?



Amortized Analysis

- O(AP) new observations inserted at leaves
- Total path length in tree bounds total work done collapsing or deleting nodes
- O(AP) amortized cost



Complexity Summary

A = Area observed
P = Number of particles

- Localization: O(AP)
  - P particles check A grid squares
  - Lookups are cached
- Map Maintenance: O(AP)
- Cost for pure localization with P particles: O(AP)

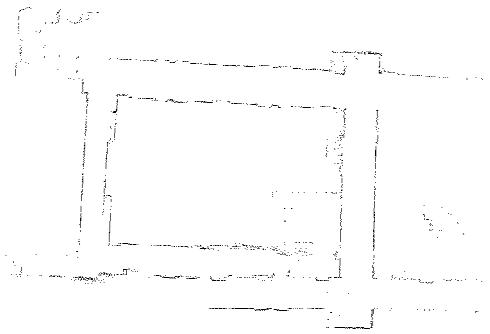
Comparison with Naïve Approach

- Total Time : O(AP)
  - Compare to O(MP)
  - M >> A

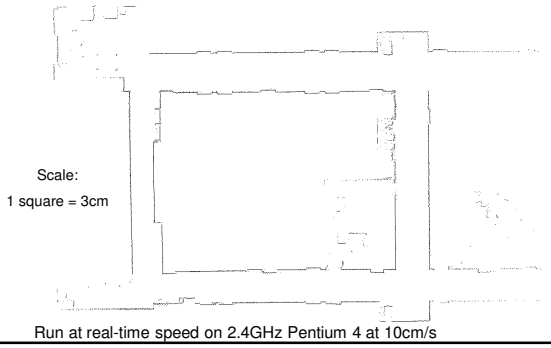
A = Area observed
P = Number of particles
M = Map size

  - Linear in observation size
  - Independent of map size
  - *Asymptotically, mapping is no more expensive than localization for fixed P*

Single Map SLAM

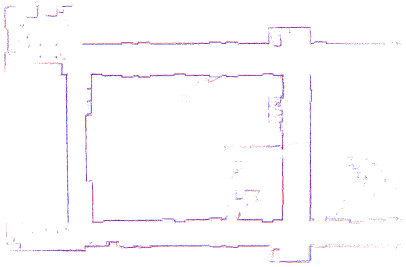


DP-SLAM 1.0 Results



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

Consistency



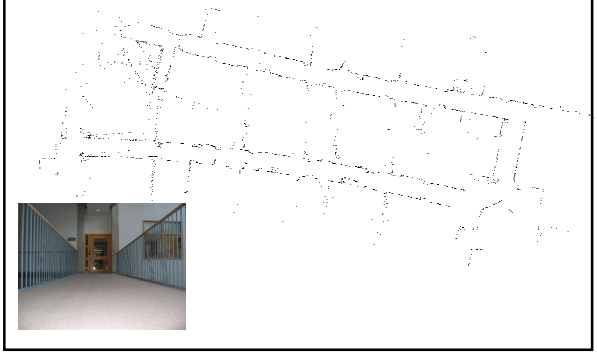
DP-SLAM 2.0

- Folds in algorithmic improvements
- Improved laser penetration model
- Models behavior of each square to laser

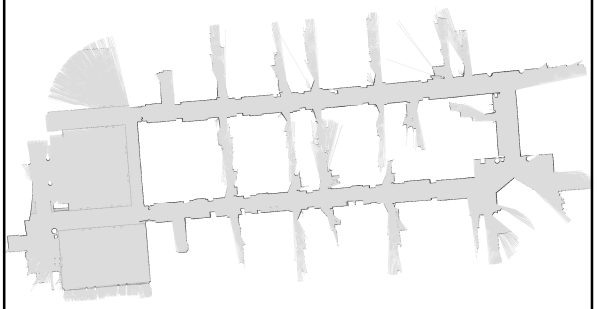
Ask for details later

- More accurate
- Can be slower in practice, but recent improvements regain real time speed

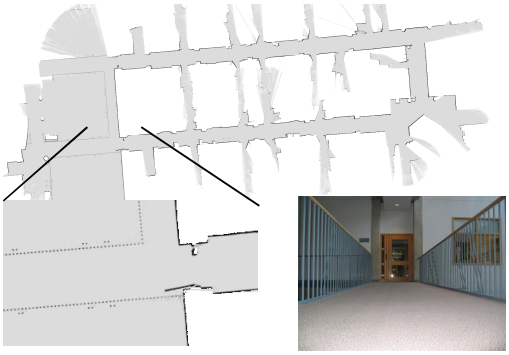
DP-SLAM 1.0 in a Noisy Domain



DP-SLAM 2.0



Close up



Caveats and Future Work

- Particle filters have limitations:
  - Still not as robust as Kalman Filter
  - Eventually, unlucky sampling will miss true state (we are working on reducing frequency/severity)
  - Can require LARGE number of particles in presence of high noise or ambiguity
- Extending to 3D (easier and harder)
- Alternate map representations

Conclusions

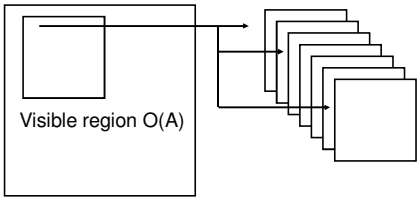
- Slam is a tracking problem
- Different approaches to tracking permit
  - Different map representations
  - Different uncertainty representations
- Good performance requires
  - Sound probabilistic inference procedures
  - Efficient data structures
  - Good modeling
- Our *per particle* mapping cost = localization cost
- Moral: Algorithms and data structures still matter ☺

Questions?

Linear Solution: Another View

- We build a local "map cache"
- Initialize O(P) local maps of size A
- For each visible grid square
  - Populate local maps from stored observations
- For each "interior" map
  - Push observations down to child maps

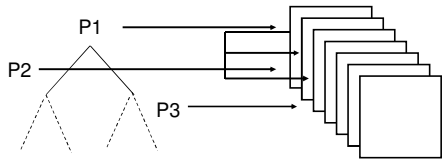
Building the Map Cache I



Global Map

Map Cache
(one entry per node in ancestry tree)
O(AP)

Building the Map Cache II



Propagate data through maps according to ancestry

Why didn't you use quad trees?

- Answer 1: Quad trees solve a *different* problem
  - Quad trees exploit homogeneity *within* a single map
  - DP-SLAM exploits homogeneity *across* maps
- Answer 2: Quad trees solve the *wrong* problem
  - Statistics collected for each grid square make grid squares for any map quite heterogeneous
- Quad trees might be useful as an *approximation* or to compress unseen regions

Laser Model

- Naïve models condition the probability of a scan on the number of squares penetrated

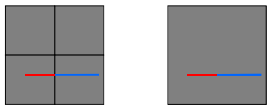
Equal length scans

One travels through six squares

The other travels through nine squares

- Probability of laser penetration depends on distance traveled through a grid square

Laser Model



- d = tendency of environment to stop laser
- Consistency
  - Scale of map should not affect probabilities
  - $P(x+y|d) = P(x|d) + (1-P(x|d))P(y|d)$

Laser Model

- Exponential distribution satisfies desiderata
  - $P(x|d) = 1 - e^{-x/d}$
- Map updates
  - Mean of $1 - e^{-x/d} = d$
  - Estimate d ~ distance observed/stops observed
- No effect on computational complexity

Why don't you have drift?

- Robot moves slowly
- Most uncertainty is short lived
  - Distant scans have most uncertainty
  - Dense scanning of close areas resolves ambiguities
- For long-lived uncertainty
  - Hierarchical approach
  - High level treats low level maps as observations
  - High level treats map errors (translations and rotations) as motion model noise