PacSLAM

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SLAM

Simultaneous Localization and Mapping

Acting in an unknown/known environment, create/update a map of the environment, while localizing on the same map

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

Chicken and egg problem

Three techniques to accurately solve SLAM:

- FastSlam
- DPSlam
- GridSlam

SLAM

Simultaneous Localization and Mapping

Often solved using particle filter approaches:

- Given particles $S=\{s_1, ..., s_m\}$, resample new states $S'=\{s_1',..., s_m'\}$

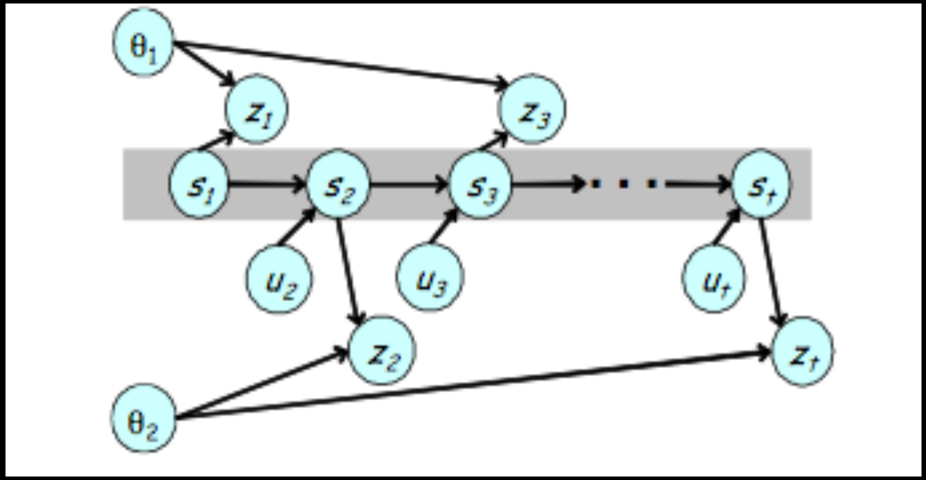
- Update the position of each particle s_m using the motion model, $P(s'' \mid s')$

- Assign a weight to each particle based on the probability of the observation, $P(o \mid s'')$

- Normalize the weights over all particles

FastSLAM

The SLAM problem:



s_t: pose of the robot

u_t: motion control model

Θ_n: positions of the landmarks

z_n: measured positions of the landmarks

Bayes Net

SLAM posterior factors:

$$p(s_t, \Theta_n | s_{t-1}, z_t, u_t) = p(s_t | s_{t-1}, z_t, u_t) p(\Theta_n | s_t, z_t, u_t)$$

FastSLAM (contd.)

- Particle Filter
  - A particle: ($w; s; \Theta_1 \ldots \Theta_n$)
  - Estimate robot pose s with probabilistic motion model, $p(s_t | s_{t-1}, z_t, u_t)$
  - Estimate parameters Θ_i of landmarks using Extended Kalman Filter (EKF), $p(\Theta_n | s_t, z_t, u_t)$
  - Weight the particles
  - Resample
- Drawback: data association problems when updating Θ

DP-SLAM

Distributed Particle SLAM

Stores only a single physical map in memory

The map stores a balanced tree at each grid location, keyed by unique particle ID numbers

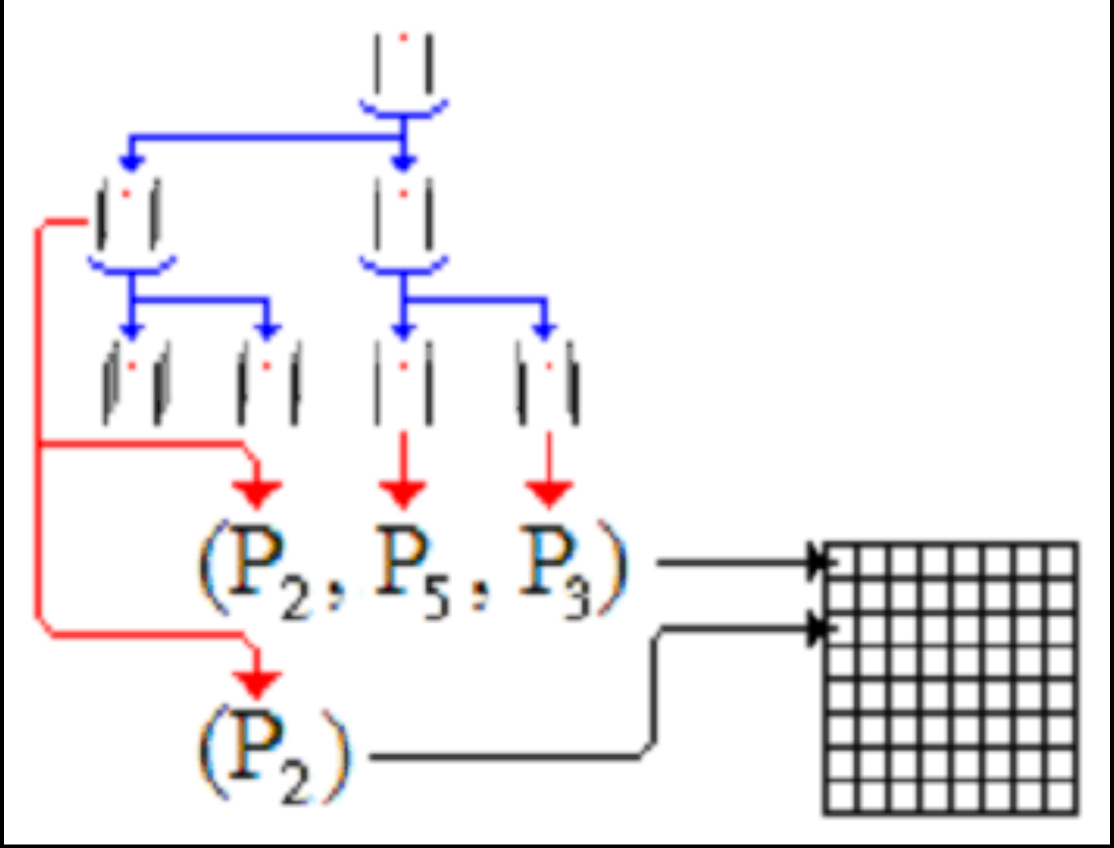
Particles update their own maps by associating data with their particle ID

Particles are stored in a particle ancestry tree

Particles only update grid squares if it causes the value to differ from the parent

DP-SLAM

Distributed Particle SLAM



GridSLAM

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

Split problem into two sub-problems:

1) Estimate robot's trajectory given observations & controls

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

2) Estimate map given robot's trajectory and observations

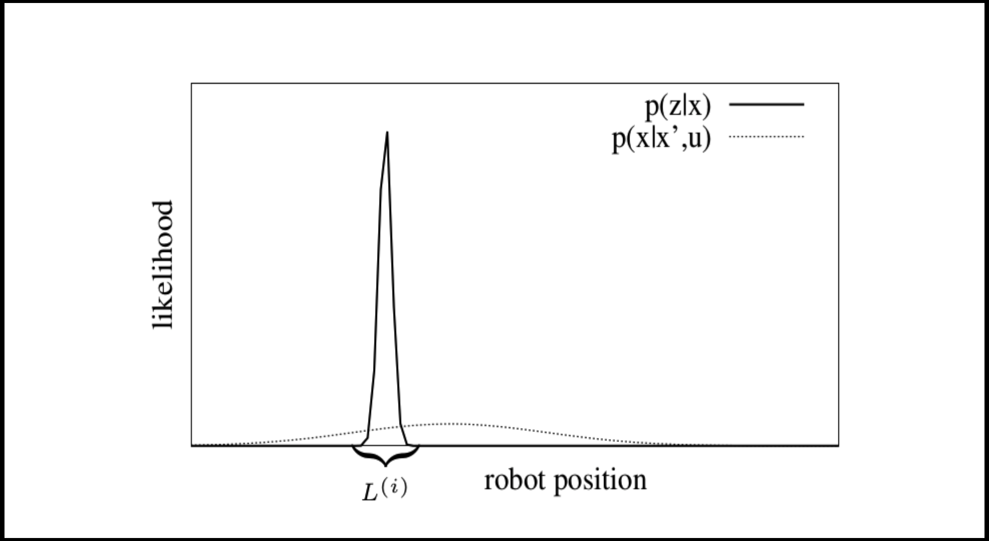
$$p(m \mid x_{1:t}, z_{1:t})$$

Use particle filter to estimate trajectory - each particle has a potential trajectory

Estimate map for each particle - "N" maps if "N" particles

GridSLAM

Two key techniques
1) Accurate sampling of particles:



2) Adaptive resampling:
Sample only when dispersion of weights is high

GridSLAM - Implementation

1) Initial guess $x_t = x_{t-1} \oplus u_{t-1}$ for robot's position from odometry
   Use encoders, IMU & Gyro

2) Scan matching: Find best pose x_t matching observation z_t to particle's map "m_{t-1}"
   Use Laser scan data & map of robot

3) Sample points around best pose from scan matching

4) Compute target distribution and sample new pose

5) Update weights, map

6)Resample if needed

Challenges & Future work

Challenges:

1) Getting SLAM to work in the pacman framework

2) Discrete nature of the pacman framework

Future work:

1) Get gridSLAM working accurately on real data & pacman world

2) Implement DP-SLAM 2.0 with probabilistic occupancy

References

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