Particle Filters

15-494 Cognitive Robotics

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Outline

- Probabilistic Robotics
- Belief States
- Parametric and non-parametric representations
- Motion model
- Sensor model
- Evaluation and resampling
- Demos

Probabilistic Robotics

- The world is uncertain:
  - Sensors are noisy and inaccurate.
  - Actuators are unreliable.
  - Other actors can affect the world.
- Embrace the uncertainty!
- How?
  - Explicitly model our uncertainty about sensors and actions.
  - Replace discrete states with beliefs: *probability distributions* over states.
  - Use Bayesian reasoning to update our beliefs.

Some Notation

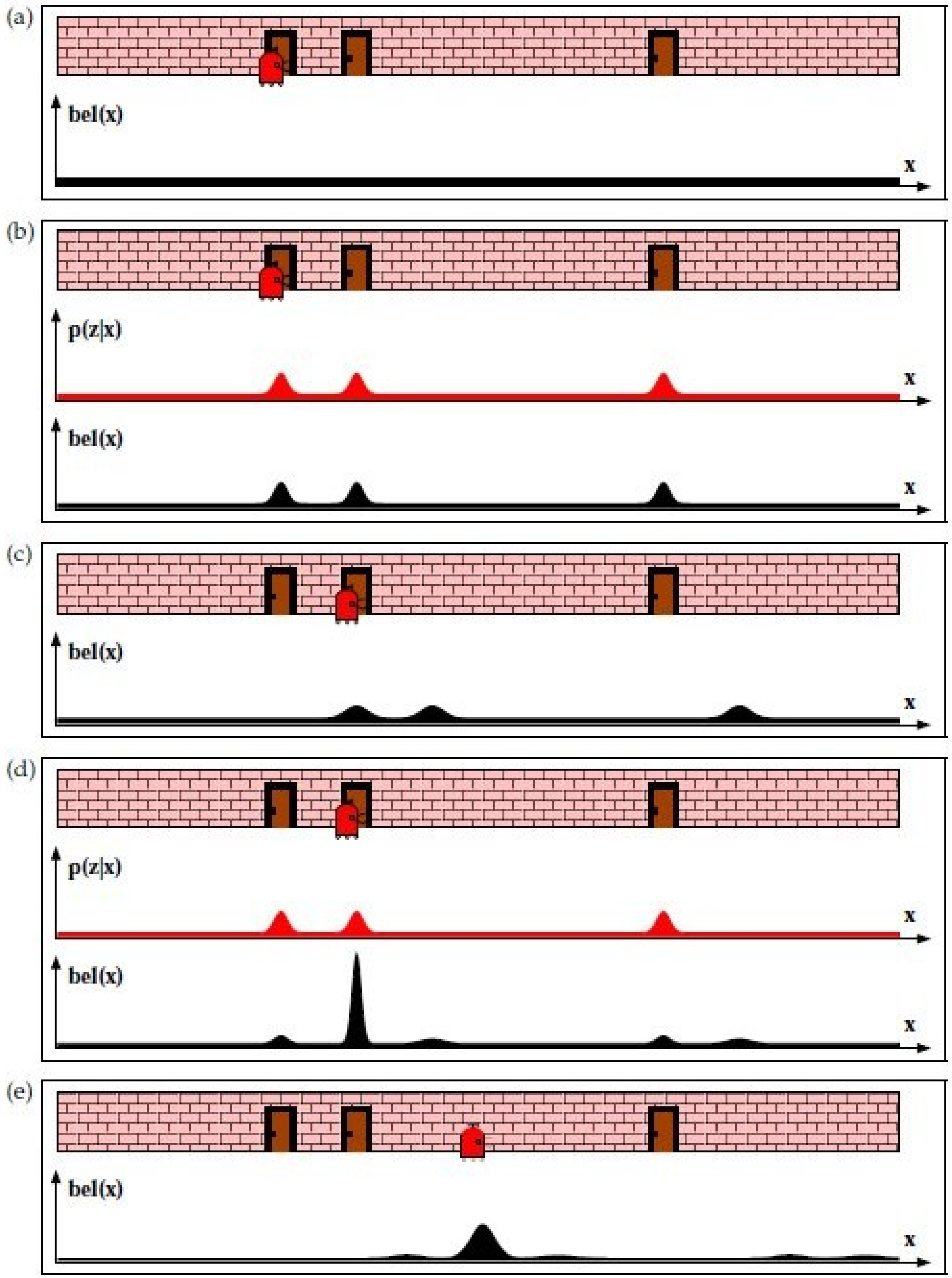
- x_t = state at time *t*
- u_t = *control signal at time t*
- z_t = *sensor input at time* t
- We don't know x_t with certainty; we have *a priori* beliefs about it:

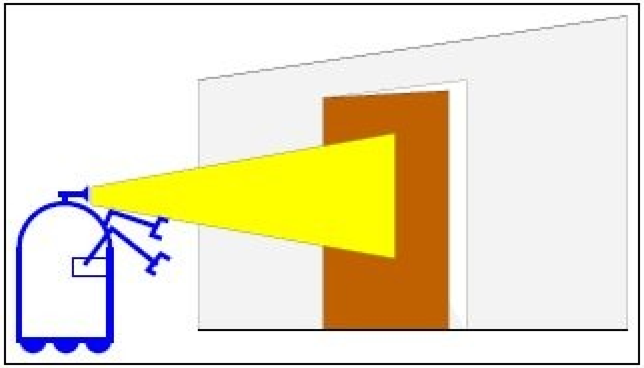
  $\overline{bel}(x_t) = p(x_t \mid z_{1:t-1}, u_{1:t})$
- New sensor data updates our belief:

  $bel(x_t) = p(z_t \mid x_t) \cdot \overline{bel}(x_t)$

Beliefs

are probability distributions





Figures from Thrun, Burgard, and Fox (2005)
Probabilistic Robotics

Parametric Representations

- Represent a probability distribution using an analytic function described by a small number of parameters.
- Most common example: Gaussian (Kalman filter)

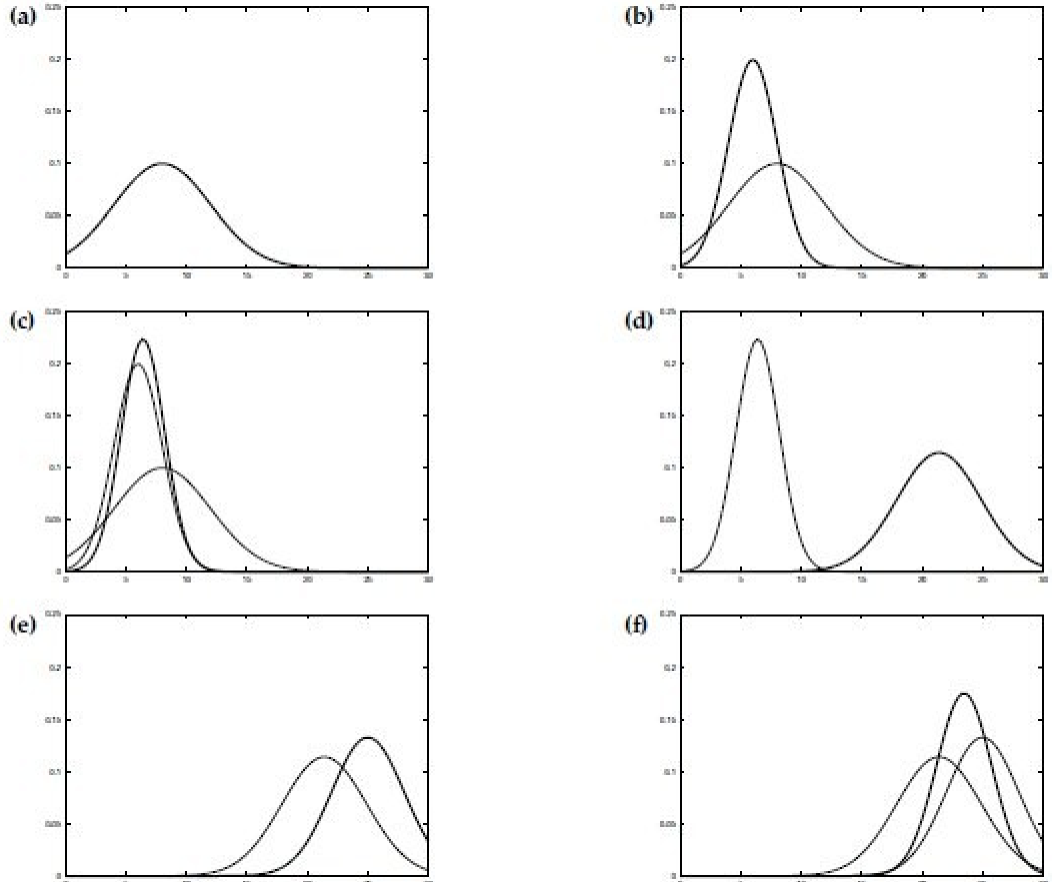


Figure from Thrun, Burgard, and Fox (2005) *Probabilistic Robotics*

Parametric Representations (2)

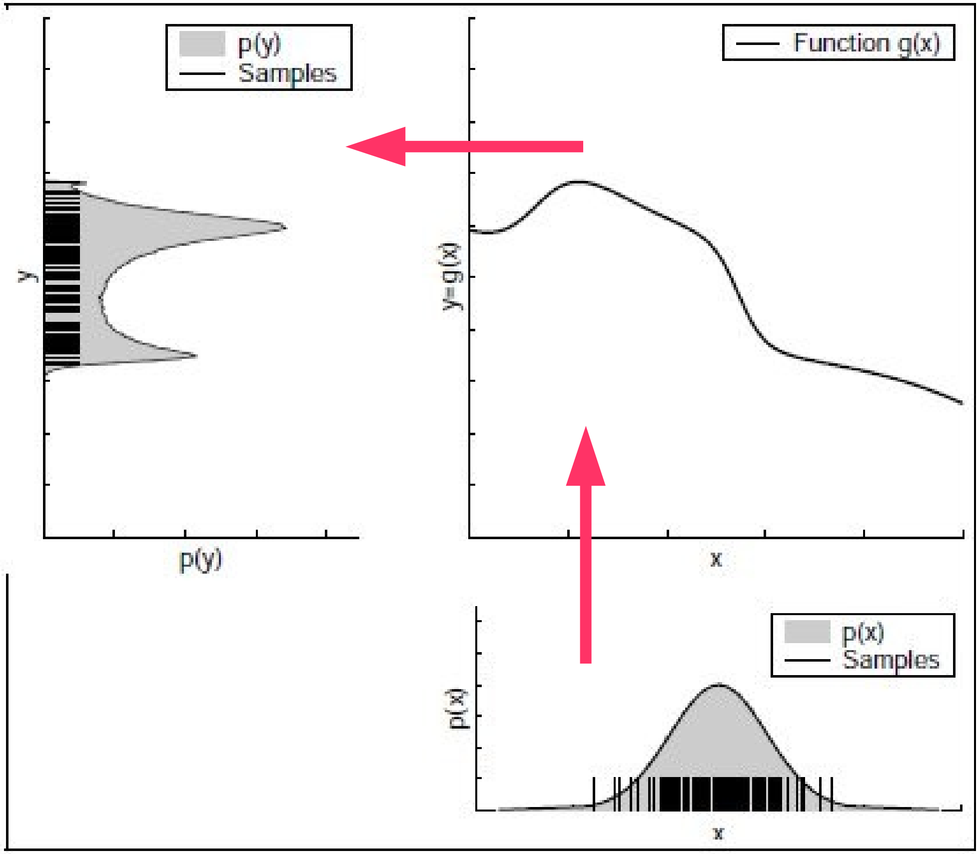
- Good points:
  - Compact representation: just a few numbers
    - For a Gaussian: mean μ and variance σ^2
  - Fast to compute
  - Nice mathematical properties
- Drawbacks:
  - May not match the data very well
  - Can give bad results if the fit is poor

Nonparametric Representations

- No preconceived formula for the distribution.
- Instead, maintain a representation of the actual distribution, via sampling.
- Example: histogram
- Good points:
  - Can represent arbitrary distributions
- Drawbacks:
  - Requires more storage
  - Expensive to update

Particle Filters

- A particle filter is a non-parametric representation of a probability distribution based on sampling.
- Each particle is a sample.
- As the distribution shifts due to new information, we resample it.

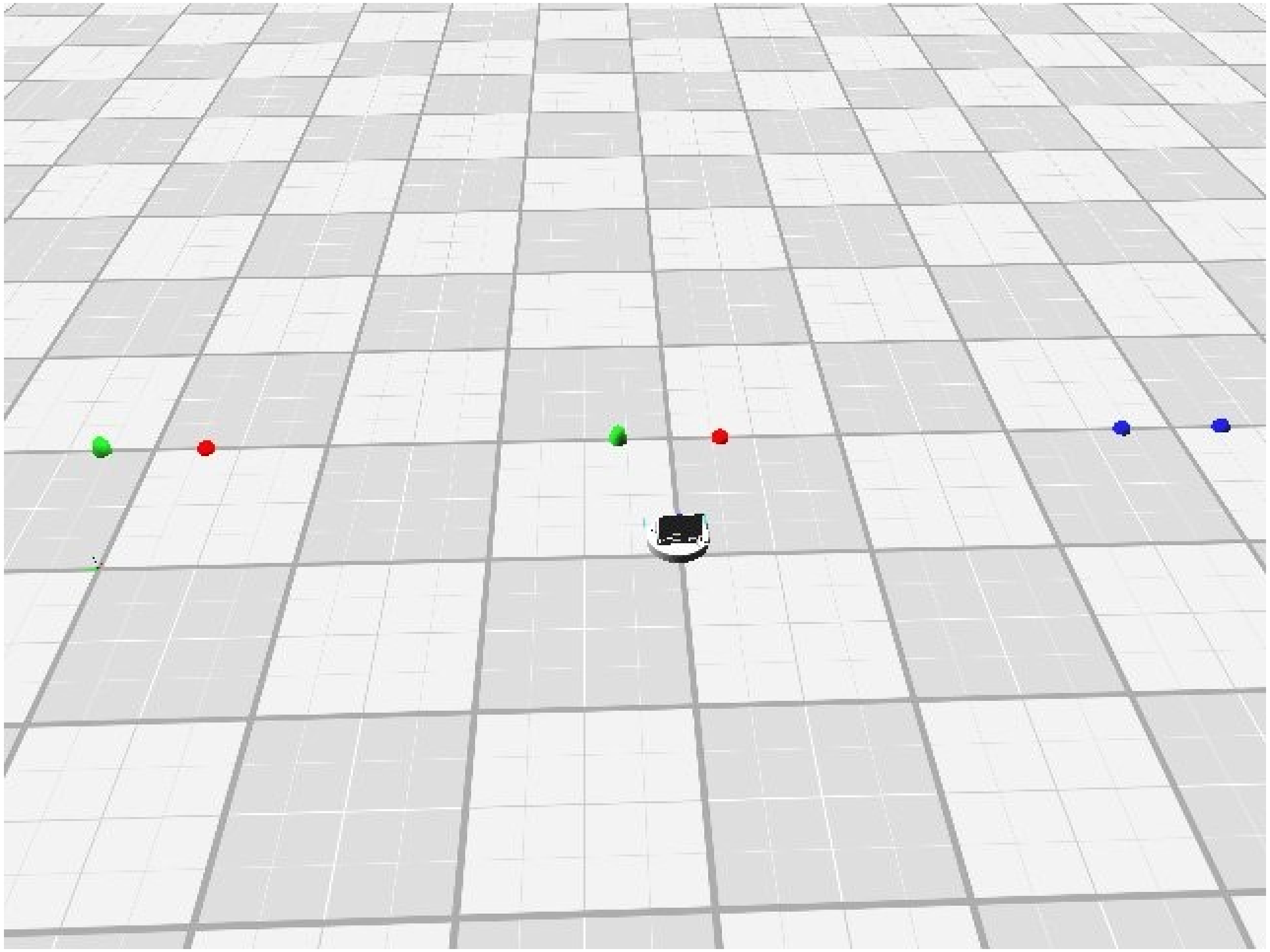


Figures from Thrun, Burgard, and Fox (2005) *Probabilistic Robotics*

Particle Filters and Localization

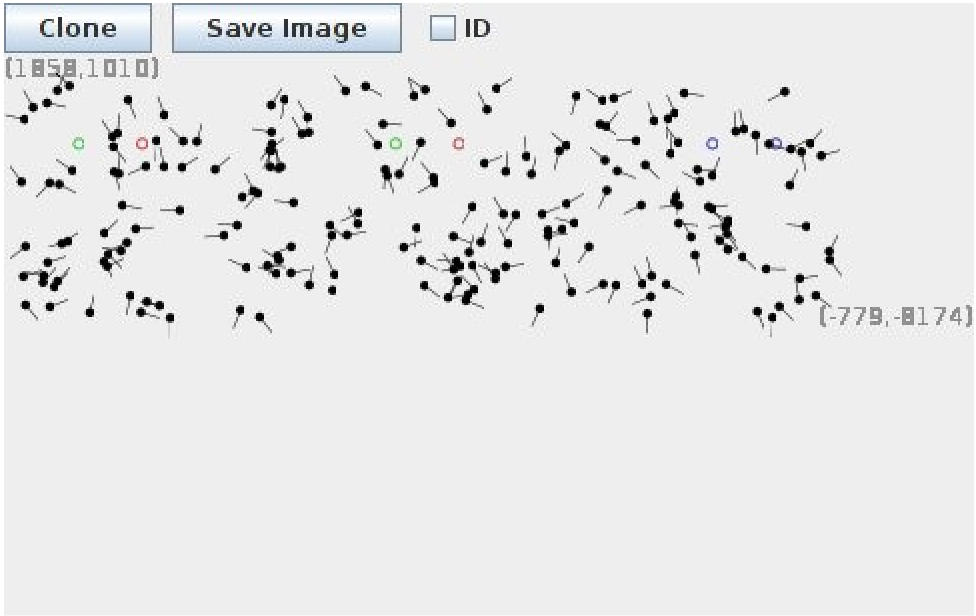
- We can use a particle filter to represent the distribution of hypotheses about the robot's pose (location and orientation).
- Two types of updates: motion, and sensor readings.
- Self-motion information (odometry) u_t:
  - Noisy: describe the noise using a motion model.
  - Drag the particles along.
- Sensor information (landmarks) z_t:
  - Noisy: describe the noise using a sensor model.
  - Weight the particles based on their sensor predictions.
  - Resample based on the weighting in order to approximate the new distribution $p(z_t|x_t) \cdot p(x_t|x_{t-1},u_t)$.

Tekkotsu Particle Filter Demo

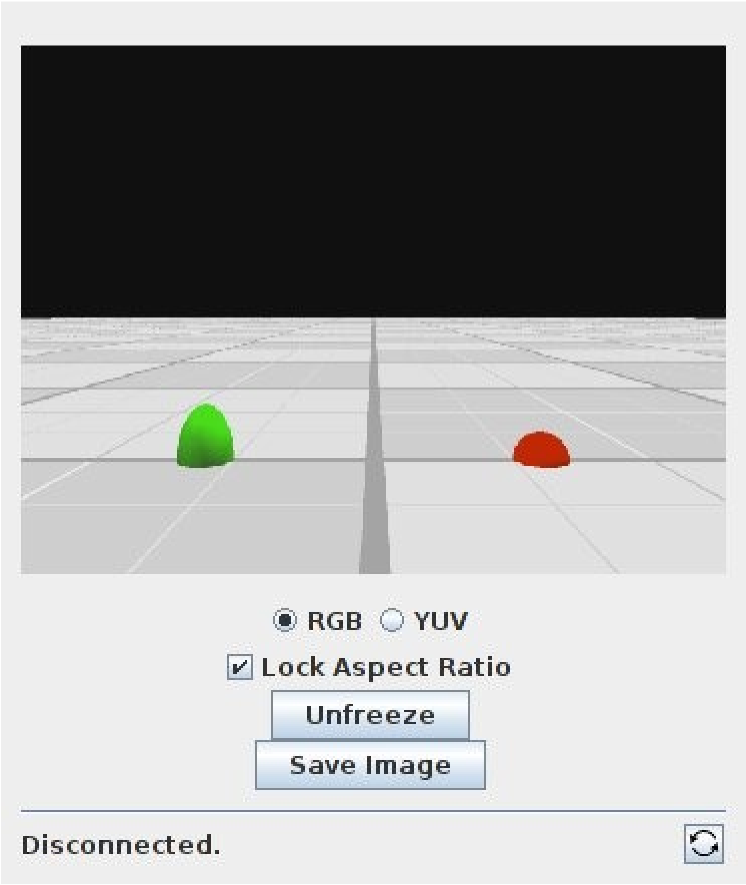


Initial World Map

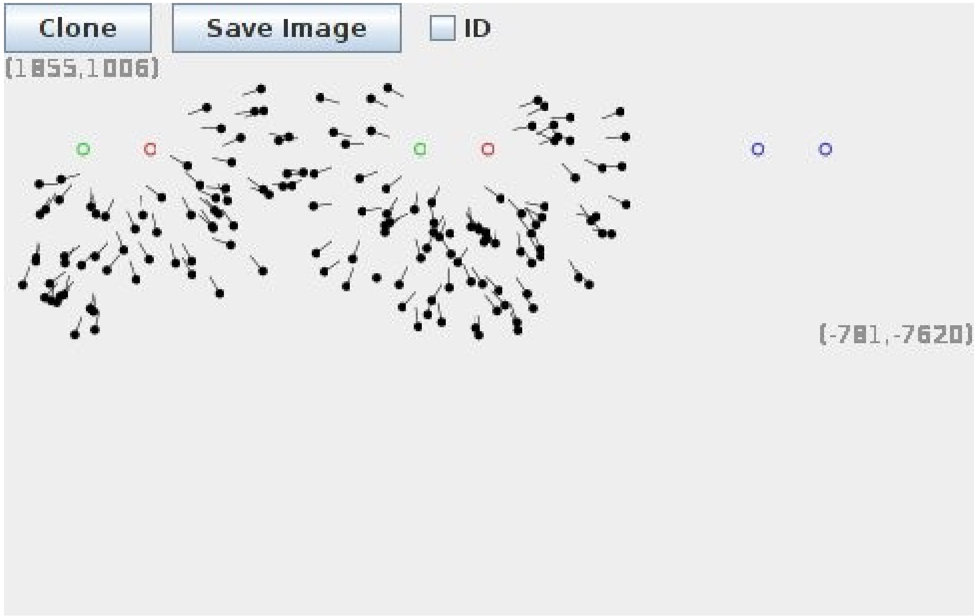
Randomize the Particles



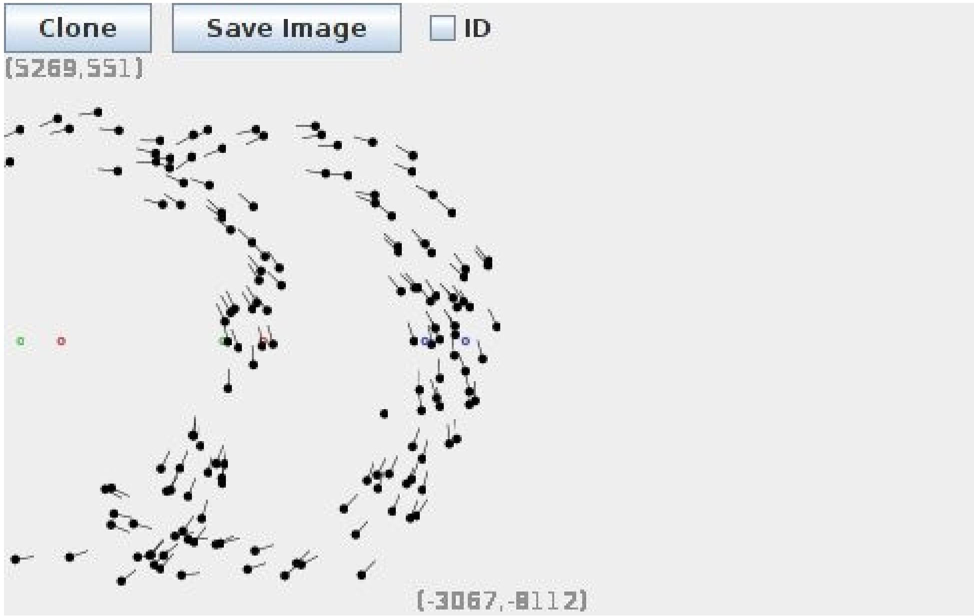
Sensor Input



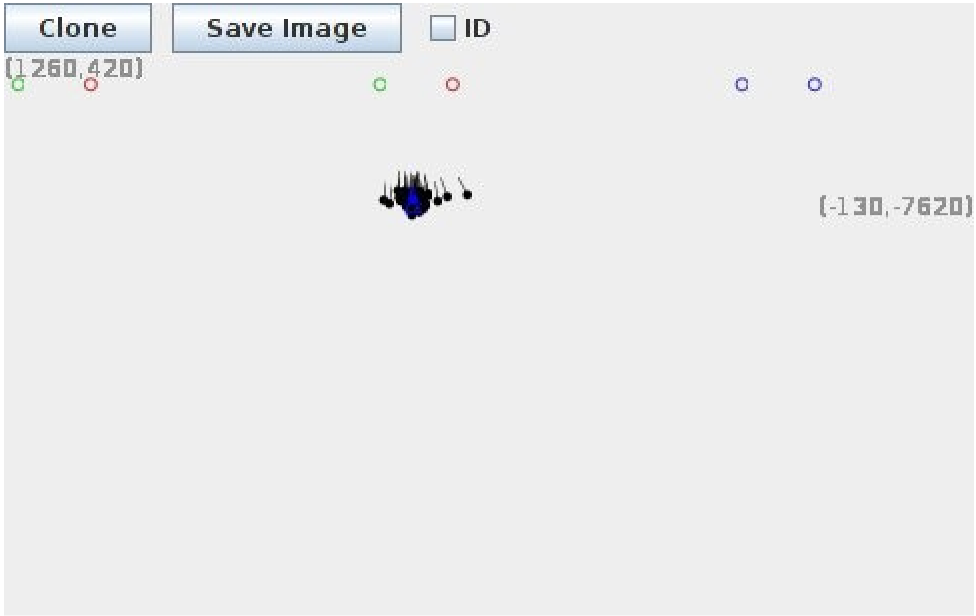
Localize



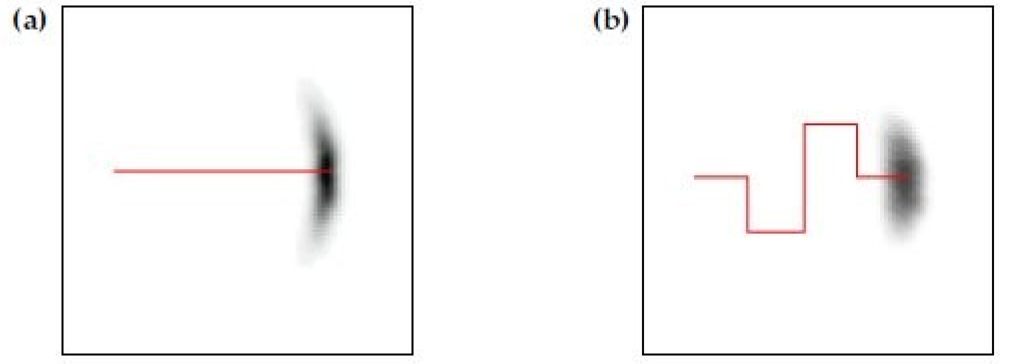
Move 3 Meters to the East



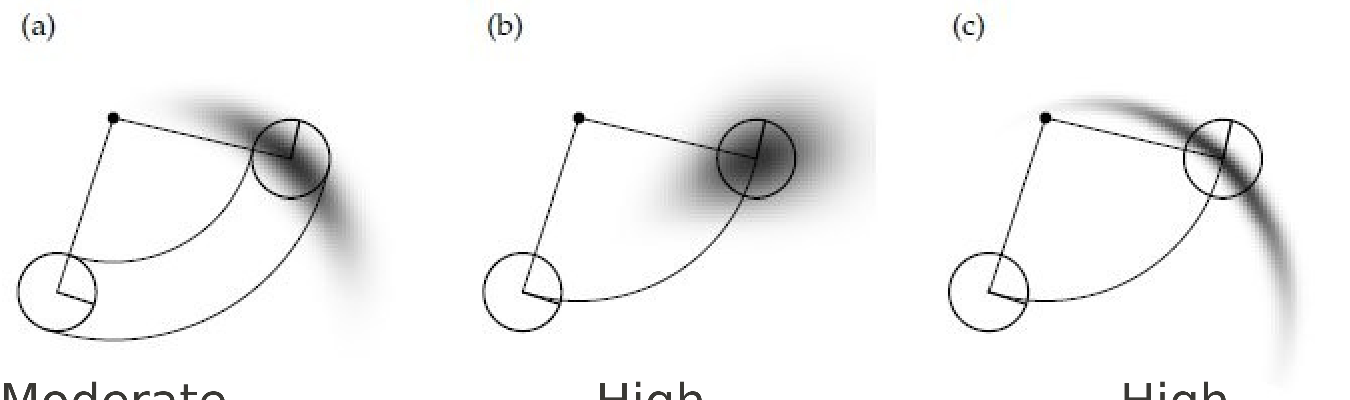
Relocalize (Cheat)



Motion Model $p(x_t|x_{t-1},u_t)$



Figures from Thrun, Burgard, and Fox (2005) *Probabilistic Robotics*



Moderate Noise Values

High Translational

High Rotational

Sensor Model

- Try to model uncertainty in sensor data.
- Lots of work on rangefinder noise models.
- For visual landmarks:
  - Distance estimates might have variance proportional to the mean.
  - Bearing estimates might have variance inversely proportional to distance.
- Tekkotsu doesn't currently implement this.

Resampling

- Resampling generates a new set of particles.
- The alternative is to keep adjusting the weights on the existing set.
- When to resample?
  - If the variance on the weights is high, then many particles are representing non-useful portions of the space.
  - Resampling redistributes the particles so they are concentrated where the probability density is highest.
- Problem: we want to sample $bel(x_t)$ but we have no representation for it. We have $\overline{bel}(x_t)$ and $p(z_t|x_t)$.
- Solution: importance sampling.

Importance Sampling

- Want to sample from f.
- Can only sample from g.
- Weight each sample by f(x) / g(x).
- The weighted samples approximate f.
- g is $\overline{bel}(x_t)$
- Weighting comes from $p(z_t|x_t)$

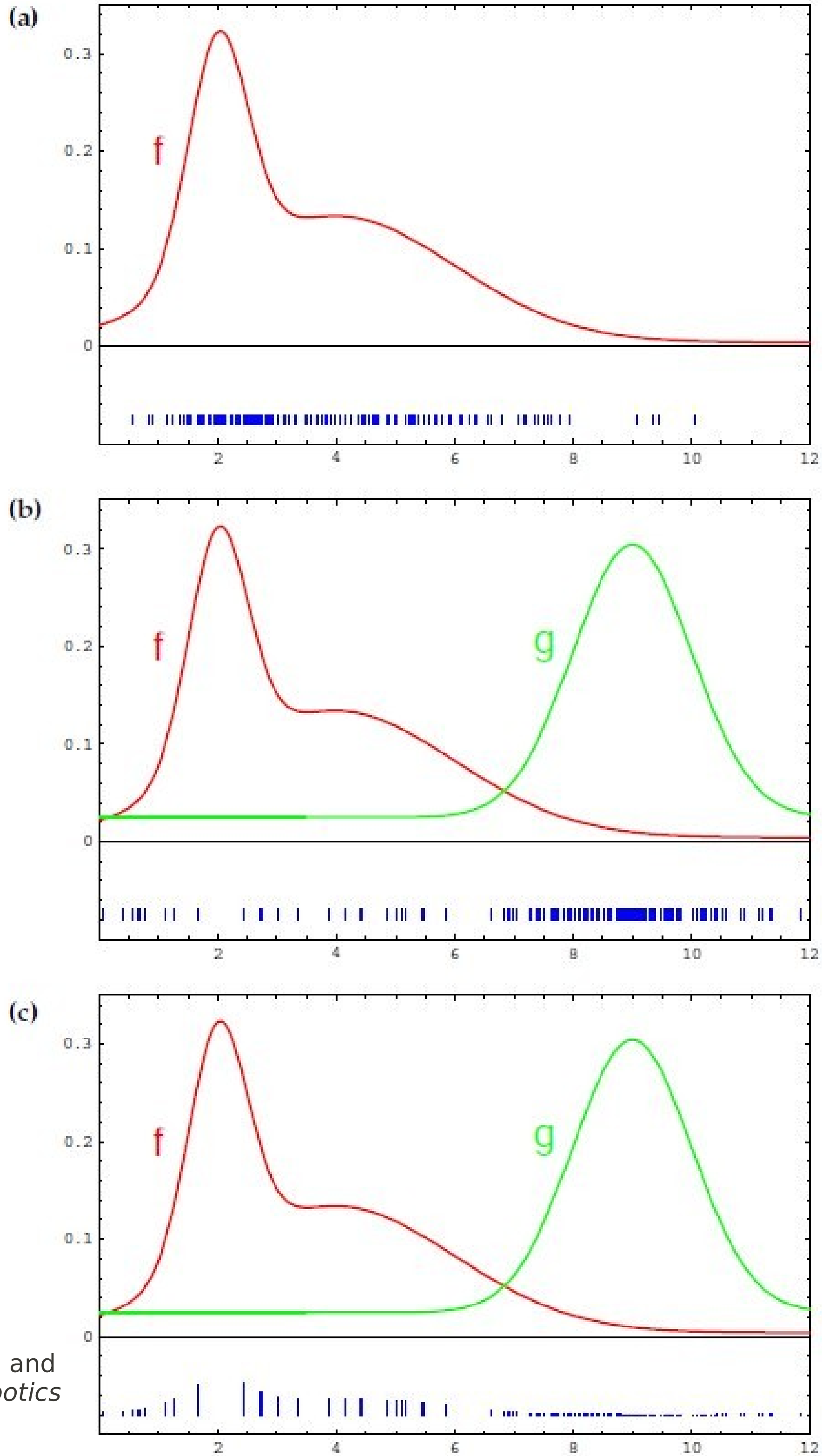


Figure from Thrun, Burgard, and Fox (2005) *Probabilistic Robotics*

Tekkotsu's Particle Filter

- Generic particle filter: templated class.

  Shared/ParticleFilter.h

- For localization:

  Localization/ShapeBasedParticleFilter.h

  Localization/LocalizationParticle.h

  Localization/CreateMotionModel.h

  Localization/ShapeSensorModel.h

Demos

- PilotDemo allows you to experiment with the particle filter. Commands:
  - rand: randomize the particles
  - loc: localize
  - disp *n*: display *n* particles

- Particle Filter Bingo (coming soon)
  - Trace the weighting of particles as sensor data comes in.