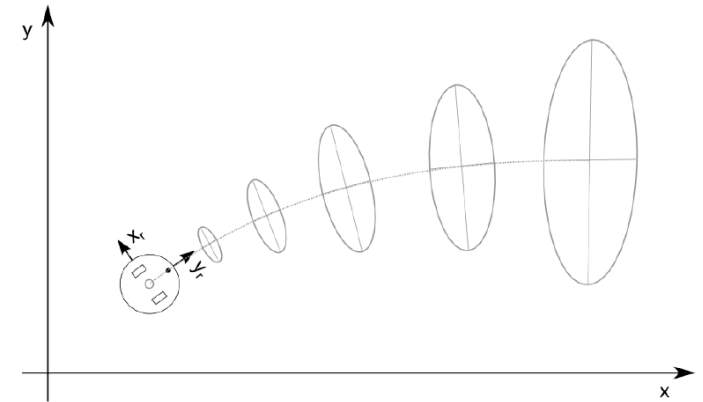


Localization

Chapter 9

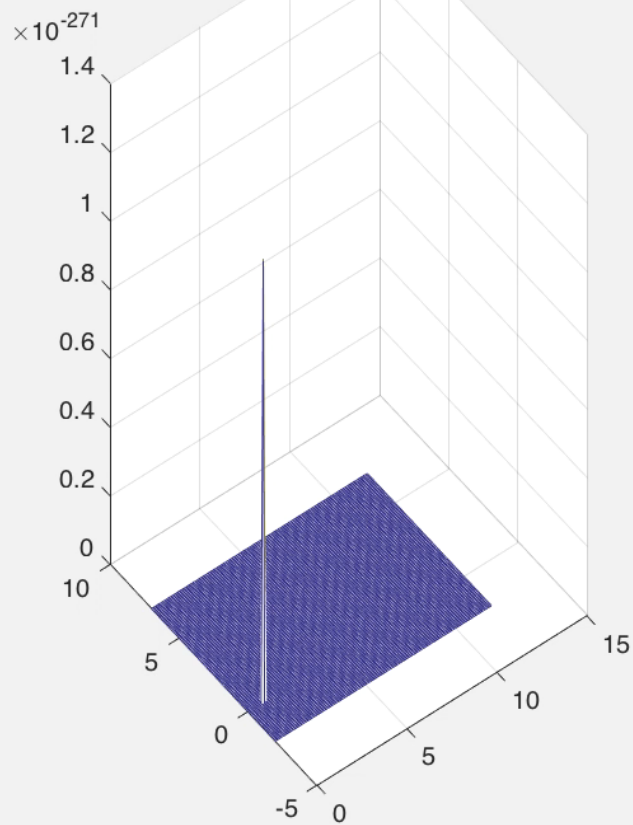
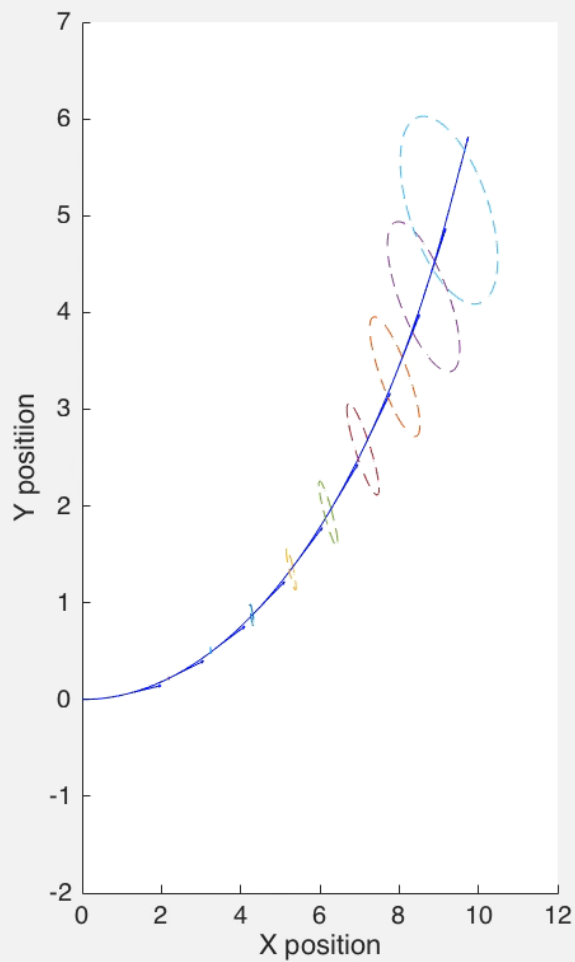
Last Week

- Random variables
- Probability distributions
 - The Uniform distribution
 - The Gaussian distribution
- Summing two random variables: convolution
- Error propagation
- Example: odometry

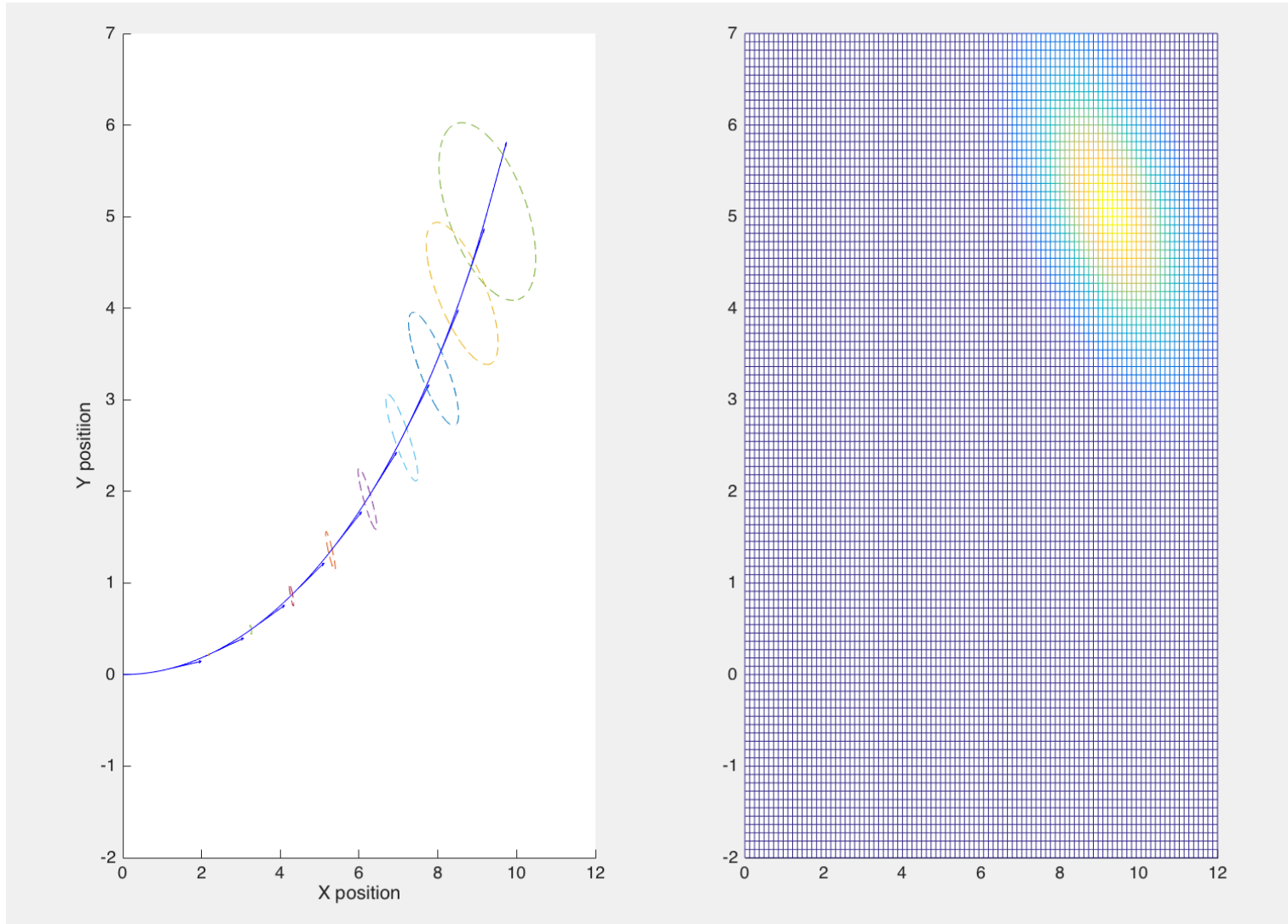


$$\sigma_y^2 = \frac{\partial df^2}{\partial x} \sigma_x^2$$

Odometry



How can we use this information?



Bayes' rule

A and B happen together

$$P(A \cap B) = P(A)P(B|A) = P(B)P(A|B)$$



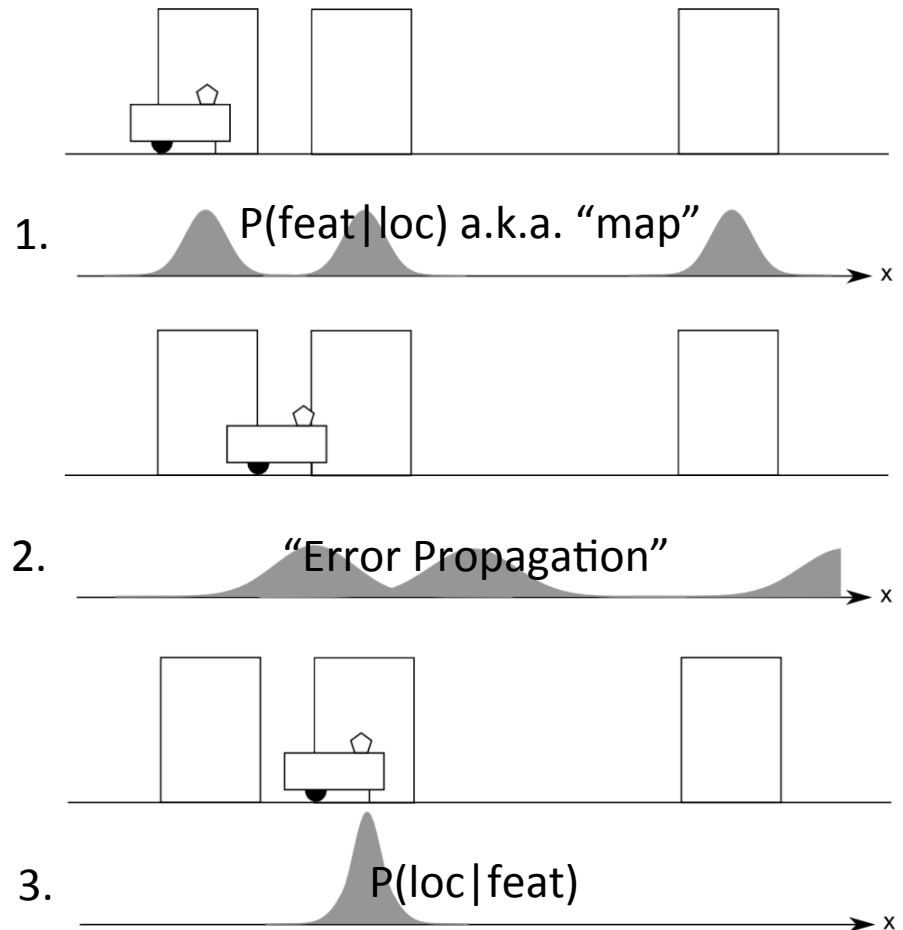
$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$

Example: Localization

$$P(loc|feat) = \frac{P(loc)P(feat|loc)}{P(feat)}$$

Need:

1. $P(loc)$: Probability to be at a location loc
2. $P(feat|loc)$: Probability to see a feature at loc
3. $P(feat)$: Normalization factor



Bayes' rule allows us to exploit perception events given a map of the environment.

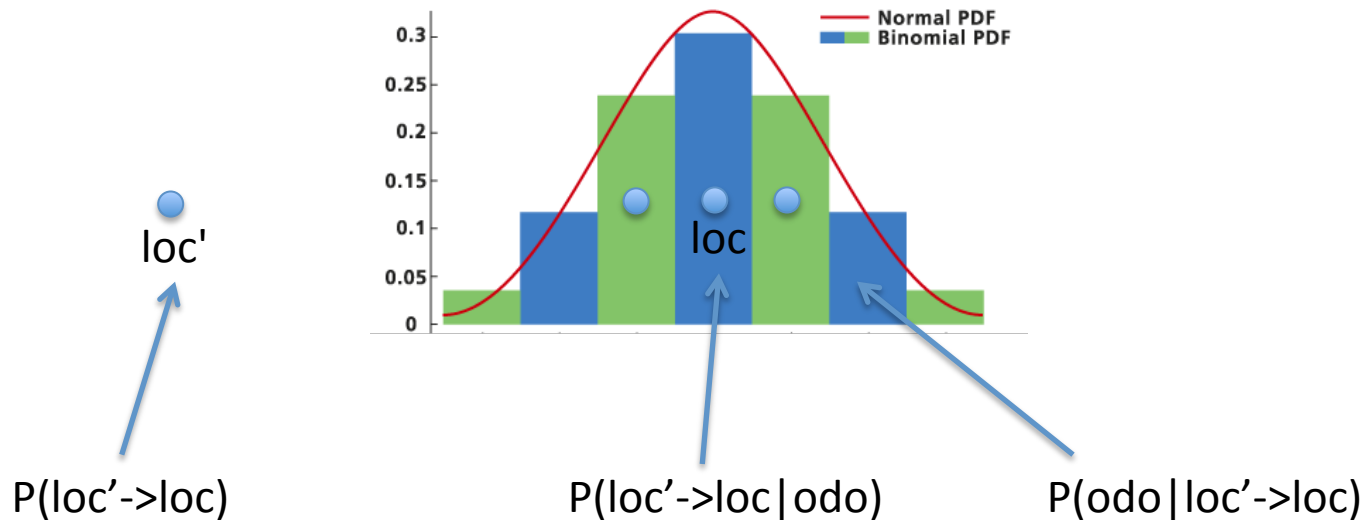
Discrete Error Propagation

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$



$$P(\text{loc}' \rightarrow \text{loc} | \text{odo}) = P(\text{loc}' \rightarrow \text{loc}) P(\text{odo} | \text{loc}' \rightarrow \text{loc}) / P(\text{odo})$$

What is the probability that I drove 1m from *loc'* to *loc*, given that my odometer told me that I drove 1m?



Problem 1: I could end up anywhere, not only at *loc*.
 Problem 2: I could have started out anywhere.

Solution

- 1. Calculate the probability to have arrived from anywhere

$$P(loc|odo) = \sum_{loc'} P(loc' \rightarrow loc) P(odo|loc' \rightarrow loc)$$

- 2. Calculate this probability for all locations

$$P(loc1|odo), P(loc2|odo), \dots$$

- => Sum of two probability distributions
Robot location * Robot Motion Model

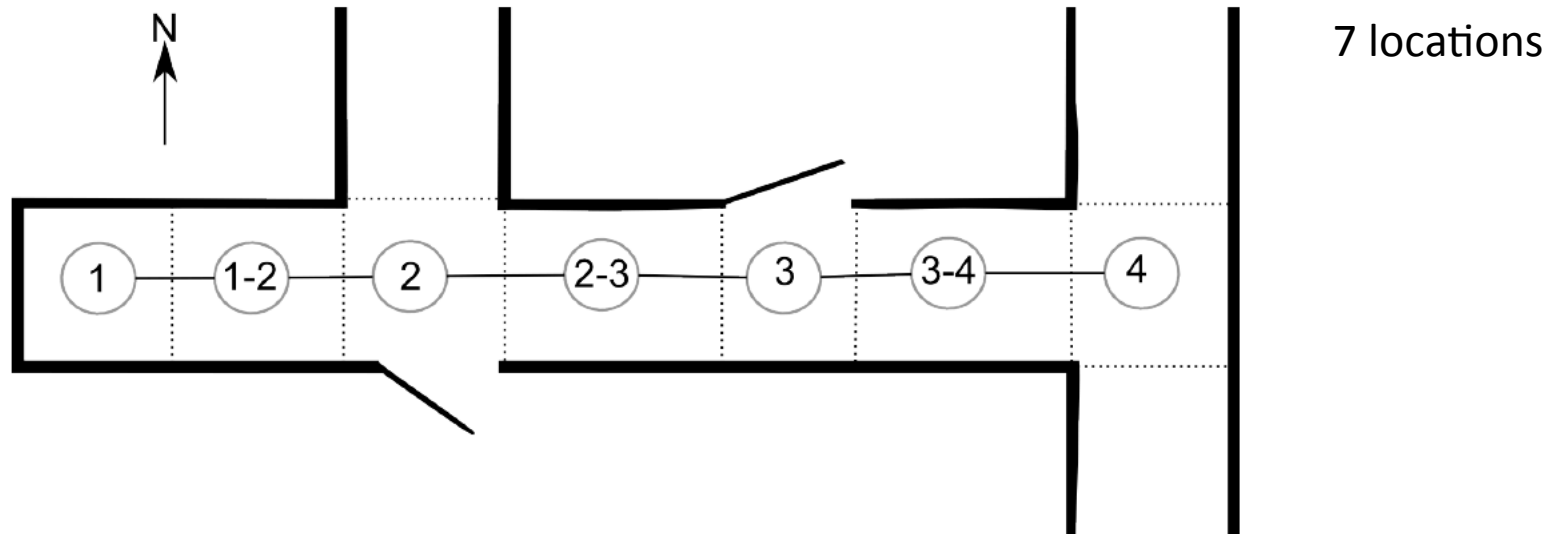
$$P(Z = z) = \sum_{k=-\infty}^{\infty} P(X = k) P(Y = z - k)$$

So far:

1. Action update: propagate the likelihood of the robot's location ("Error propagation")
2. Perception update: use Bayes' rule to update posterior probability $P(loc/feat)$ using knowledge about where features are

This is known as *Markov Localization*. Problem: How to deal with sensor uncertainty?

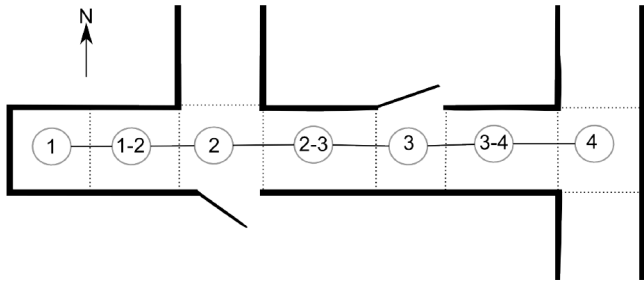
1D Example (Nourbaksh, 1994)



Features and their likelihood $P(\text{feat}|\text{loc})$

	Wall	Closed dr	Open dr	Open hwy	Foyer
Nothing detected	70%	40%	5%	0.1%	30%
Closed door detected	30%	60%	0%	0%	5%
Open door detected	0%	0%	90%	10%	15%
Open hallway detected	0%	0%	0.1%	90%	50%

Example



1. Initialization $P(1-2)=0.8$ and $P(2-3)=0.2$
2. Robot drives east until it reports
“open hallway left and open door to its right”

	Wall	Closed dr	Open dr	Open hwy	Foyer
Nothing detected	70%	40%	5%	0.1%	30%
Closed door detected	30%	60%	0%	0%	5%
Open door detected	0%	0%	90%	10%	15%
Open hallway detected	0%	0%	0.1%	90%	50%

1. Perception update:

$P(\text{feat} | 1) = 0$; $P(\text{feat} | 1-2) = 0$; **$P(\text{feat} | 2) = 0.9 * 0.9$** ; $P(\text{feat} | 2-3) = 0$; $P(\text{feat} | 3) = 0$; $P(\text{feat} | 3-4) = 0$; **$P(\text{feat} | 4) = 0.9 * 0.1$**

2. Action update:

$P(2 | \text{feat}) = P(2)P(\text{feat} | 2) = \mathbf{0.8 * 0.81 = 64.8\%}$

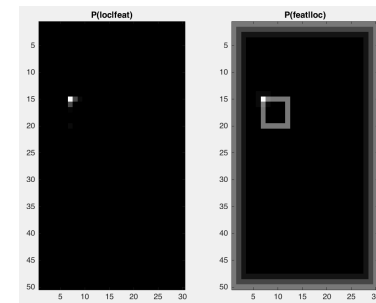
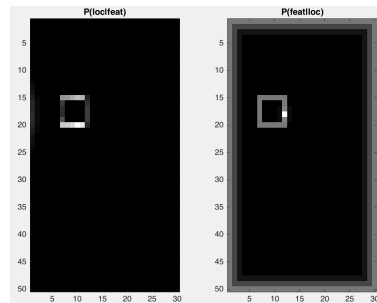
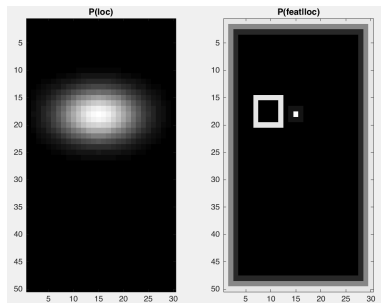
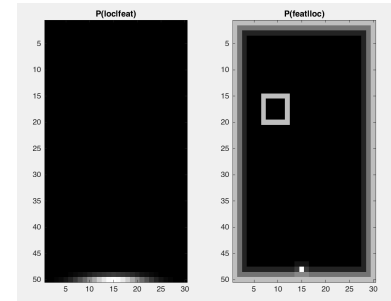
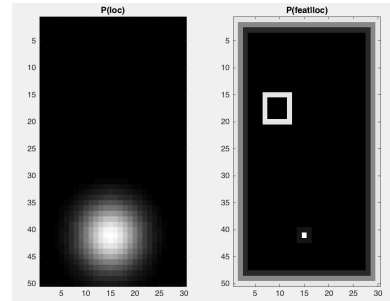
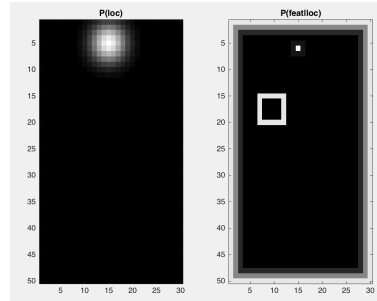
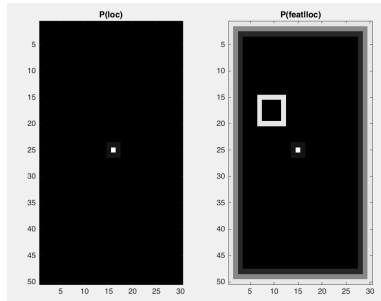
$P(4 | \text{feat}) = P(4) * P(\text{feat} | 4) = (\mathbf{0.2 * 0.05 * 0.7 * 0.7 * 0.7} + \mathbf{0.8 * 0.001 * 0.05 * 0.7 * 0.7 * 0.5 * 0.7 * 0.7 * 0.7}) * P(\text{feat} | 4) = 0.03\%$

3. Normalize

$P(2) = 99.95\%$

$P(4) = 0.005\%$

2D Example



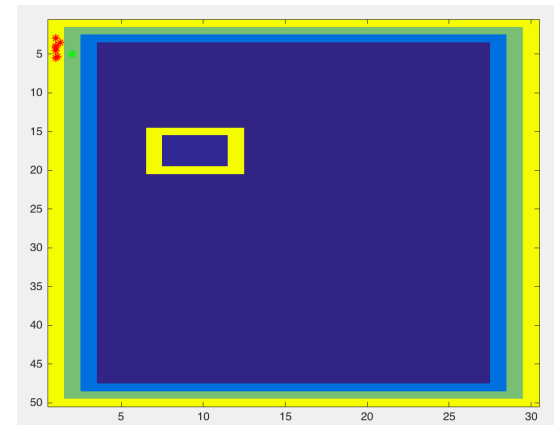
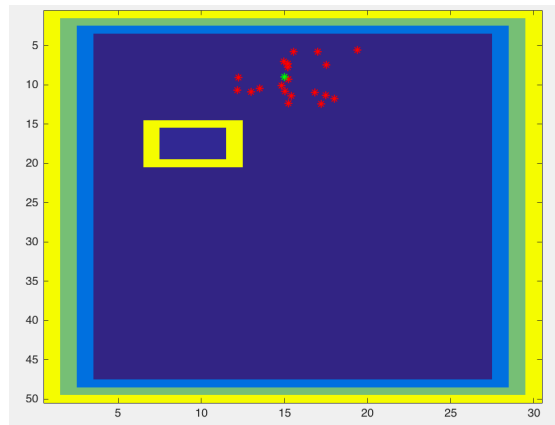
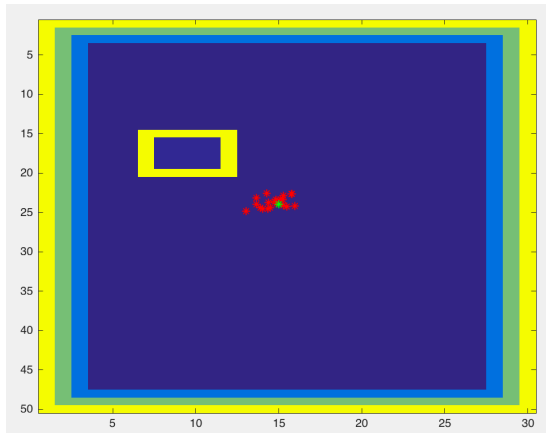
Problem: Need to update the probability for every cell on the map, which is very inefficient and does not scale.

(Matlab demo)

Solution: Sampling-based approach (Particle Filter)

1. Sample random “particles” around possible belief candidates
2. Action update: move particles like the robot, add noise using its motion model
3. Perception update: evaluate the likelihood of each particle to generate this perception event
4. Bookkeeping: remove unlikely particles and replicate likely ones

Demo



Summary

- Bayes' rule provides a formal framework to use information about known features in a map
- Together with “error propagation” this is known as “Markov Localization”
- The problem can be computationally simplified using a “Particle Filter”
- Both are very general methods for state estimation, not limited to localization
- Both approaches are able to solve the “dropped robot” problem