Introduction to Localization

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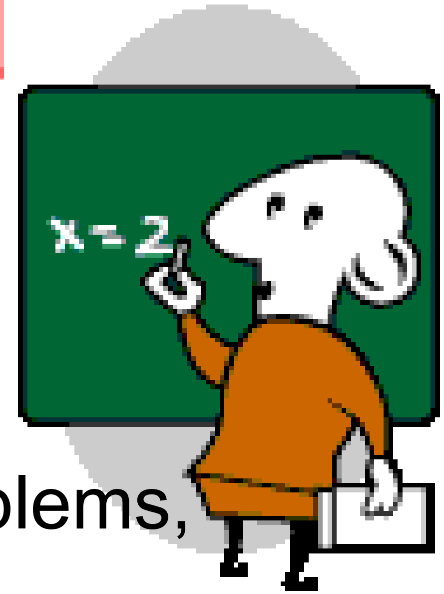
Lecture slides heavily use material from the textbook and
Sebastian Thrun, Lecture Slides; http://www.probabilistic-robotics.org/

What we will discuss



- Define *Localization* problems,
- Note the fundamental difficulty of localization,
- Present a taxonomy of localization problems,
- Discuss relative difficulties,
- Markov Localization,
- Discuss our fundamental need to go further…

Mobile Robot Localization

- A important canonical problem of mobile robotics.
- **What is it?**

Determine (estimate) the *pose* $x_t=(x\ y\ \theta)$ of a robot relative to a *given map* (*m*) of an environment!

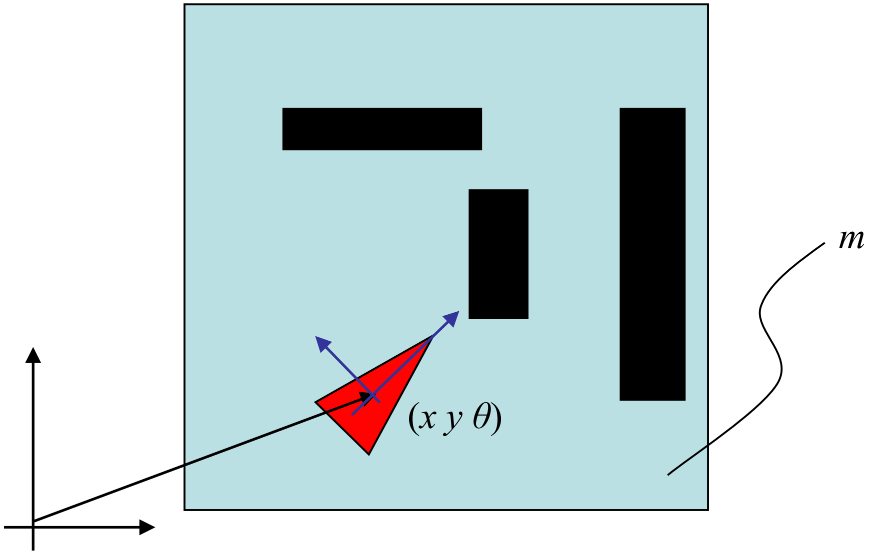
Determine (estimate) a coordinate transformation

(between the global world frame (map coordinate system) and the local robot frame (where the sensors operate)

Two alternate views

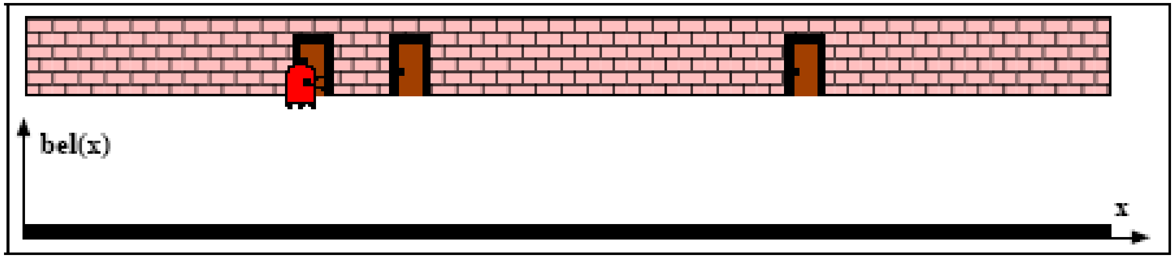
Localization

- If pose (state) $\mathbf{x}_t$=($x\ y\ \theta$) was known…
- No localization problem!
- The coordinate tranformation can readily be specified (assuming $\mathbf{x}_t$ is expressed in the same global coordinate frame as the map *m*).



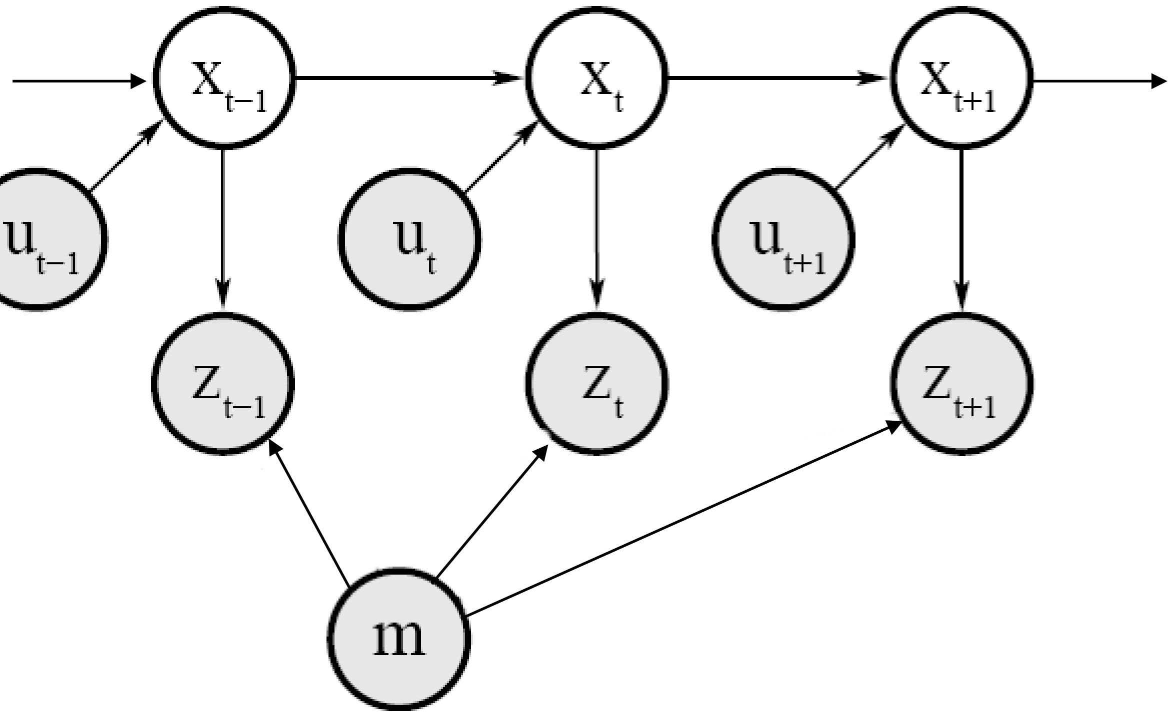
Fundamental Difficulty

- *Pose* (or *state* in general) is usually not directly measurable by the mobile robot,
- It needs to be *inferred* from measurement data,
- **Usually over a collection of successive sensor measurements.**



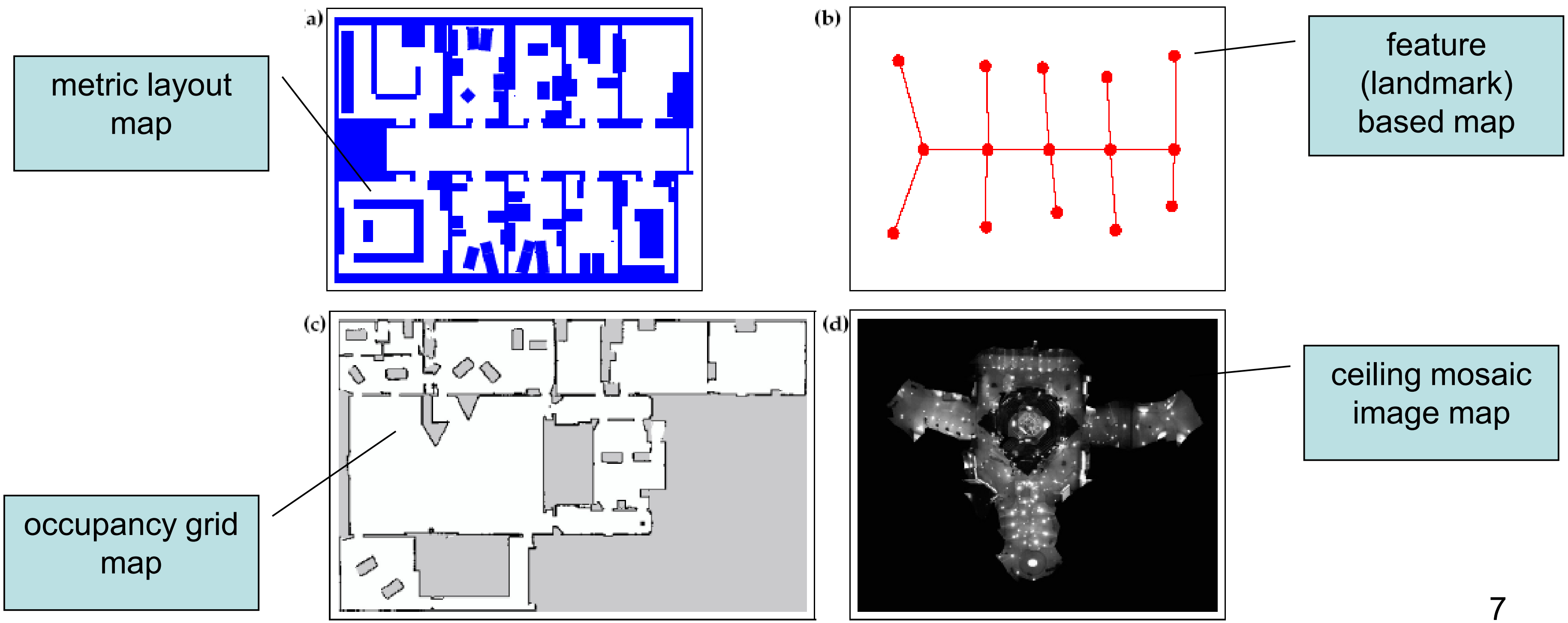
DBN of Localization Process

- Remember the Dynamic Bayesian Network representing the probabilistic relation between states, controls and observations:



Relation with Map Representation

- Map representations will later be discussed further,
- Different localization approaches based on different map representations:

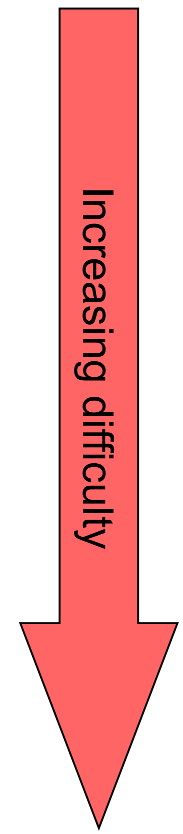


A “taxonomy” of Localization

- **In relation to the *nature of the environment* and the *initial knowledge*:**
  - ***Local* versus *Global* localization,**
    (Position tracking, global localization, kidnapped robot problem)
  - ***Static* versus *Dynamic* environments,**
    (Persistent vs transient changes, state augmentation, filtering)
  - ***Passive* versus *Active* approaches,**
    (observation only versus active control for better localization)
  - ***Single robot* versus *Multi-robot*.**
    (belief representation and information sharing - communication)

Local versus Global

- **Local problem (*position tracking* or *tracking*),**
  - Assumes known initial pose,
  - Small noise due to sensors and motion,
  - Unimodal Gaussian densities appropriate
- **Global localization**
  - Unknown initial pose but robot knows it is lost,
  - Large initial uncertainty,
  - Multi-modal or non-parametric densities required
- **Kidnapped Robot Problem**
  - Robot does not even know it is lost!!



Static versus Dynamic

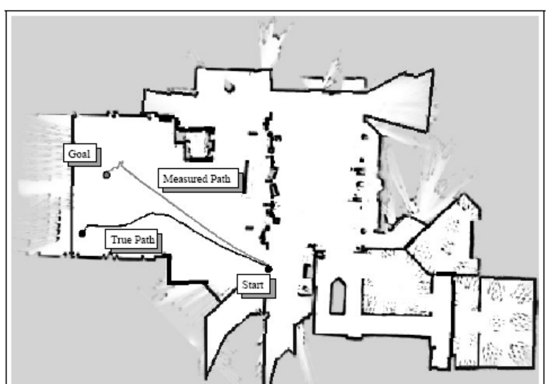
- **Static Environments**
  - The only changing variable is robot *pose* (or *state*),
  - All other aspects of env. (map, other entities) static,
  - Nice properties and efficient solutions…
- **Dynamic Environments**
  - Other entities whose state changes with time,
  - Persistent changes (standing humans, doors, furniture),
  - Transient changes (fast moving humans, vehicles)
- **Handling Dynamic Environments**
  - State augmentation (increased complexity),
  - Pure noise treatment (for fast transients),
  - Measurement Filtering (validation)

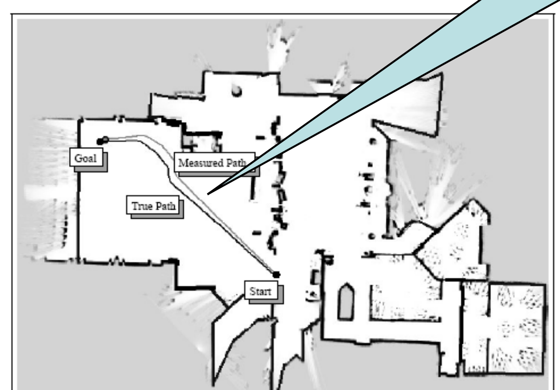
Increasing difficulty

Passive versus Active Approaches

- **Can Localization take control of the motion of the Robot?**
- **Passive approaches: Localization is an *observer*,**
- **Active approaches: Localization may take control of the robot motion to:**
  - *Minimize error* of localization,
  - *Minimize costs* associated with localization errors
  - Remember: Coastal Navigation

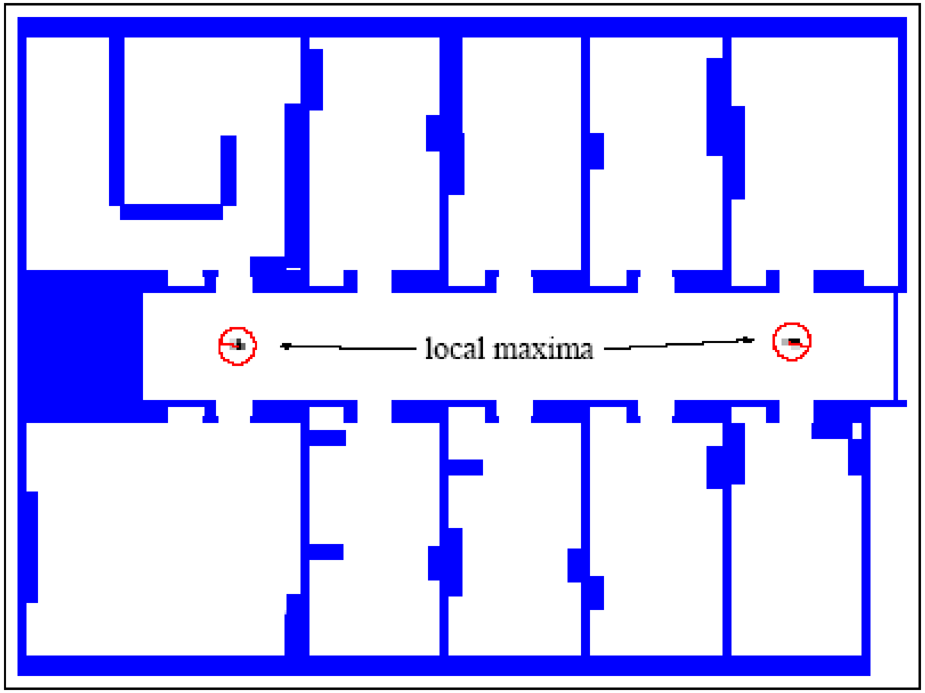
Robot is navigated to stay close to the map features hence stay localized





Active Approach Example

- What is happening here?
- How to solve it?



Single versus Multi-Robot

- **Single-robot most common,**
- **Multi-robot is increasingly an active area,**
- **Team of Robots in an area:**
  - Can be solved for individual robots as before, but…
  - What if robots can detect each other?
  - What if robots can communicate and share belief?
- **Collaboration raises interesting and non-trivial research questions…**

Markov Localization

- **Probabilistic localization algorithms are all variants of the *Bayes Filter,***
- ***Markov Localization* is direct extension of the Bayes Filter to *Localization* problem:**

Algorithm Markov_localization$(bel(x_{t-1}), u_t, z_t, m)$**:**
for all x_t do
$\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}, m)\, bel(x_{t-1})\, dx$
$bel(x_t) = \eta\, p(z_t \mid x_t, m)\, \overline{bel}(x_t)$
endfor
return $bel(x_t)$

Algorithm Bayes_filter$(bel(x_{t-1}), u_t, z_t)$**:**
for all x_t do
$\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1})\, bel(x_{t-1})\, dx_{t-1}$
$bel(x_t) = \eta\, p(z_t \mid x_t)\, \overline{bel}(x_t)$
endfor
return $bel(x_t)$

Markov Localization Example

- **Remember?**

Algorithm Markov_localization($bel(x_{t-1}), u_t, z_t, m$):

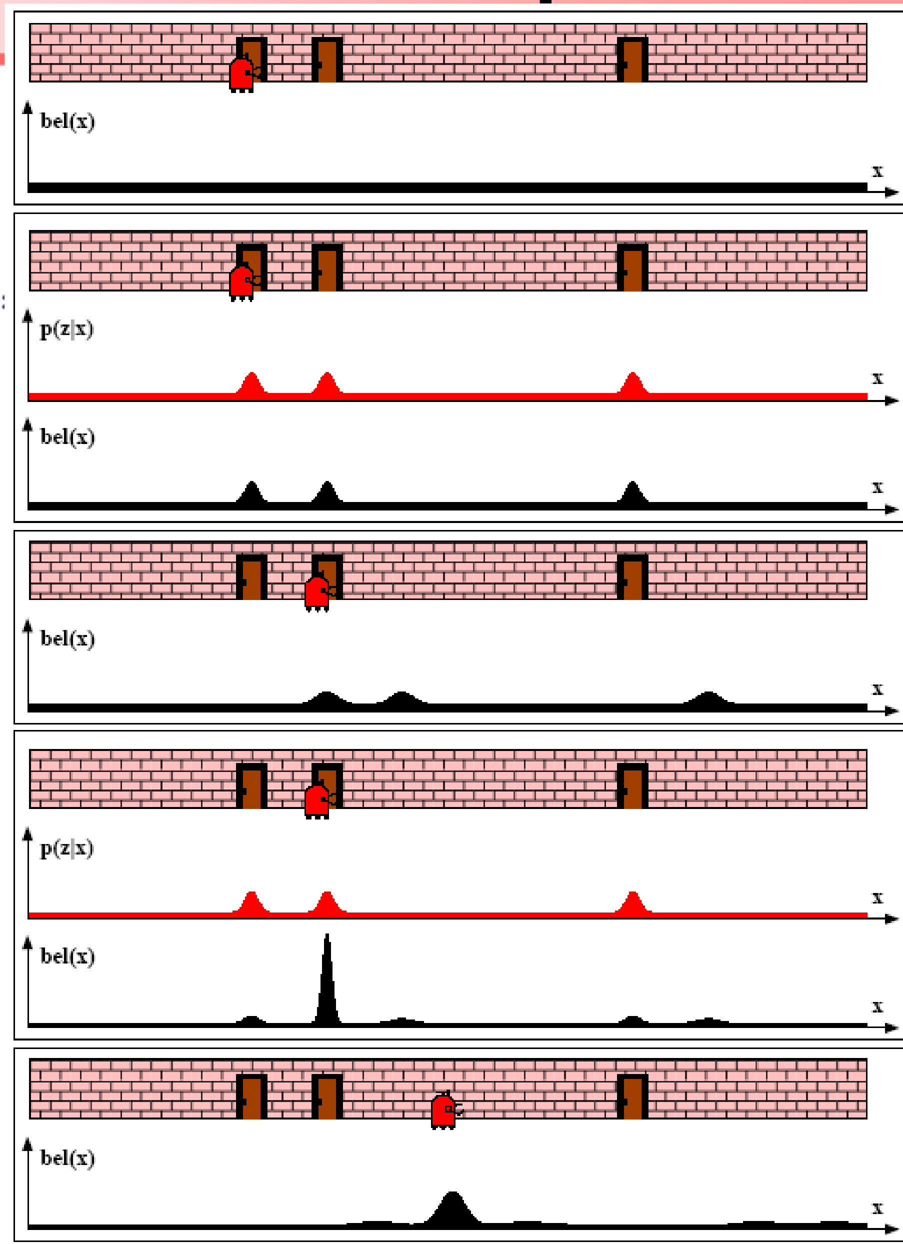
    for all x_t do

        $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}, m)\ bel(x_{t-1})\ dx$

        $bel(x_t) = \eta\ p(z_t \mid x_t, m)\ \overline{bel}(x_t)$

    endfor

    return $bel(x_t)$



Where do we go from here?

- **Appears like we cannot go any further before being able obtain these “models”:**

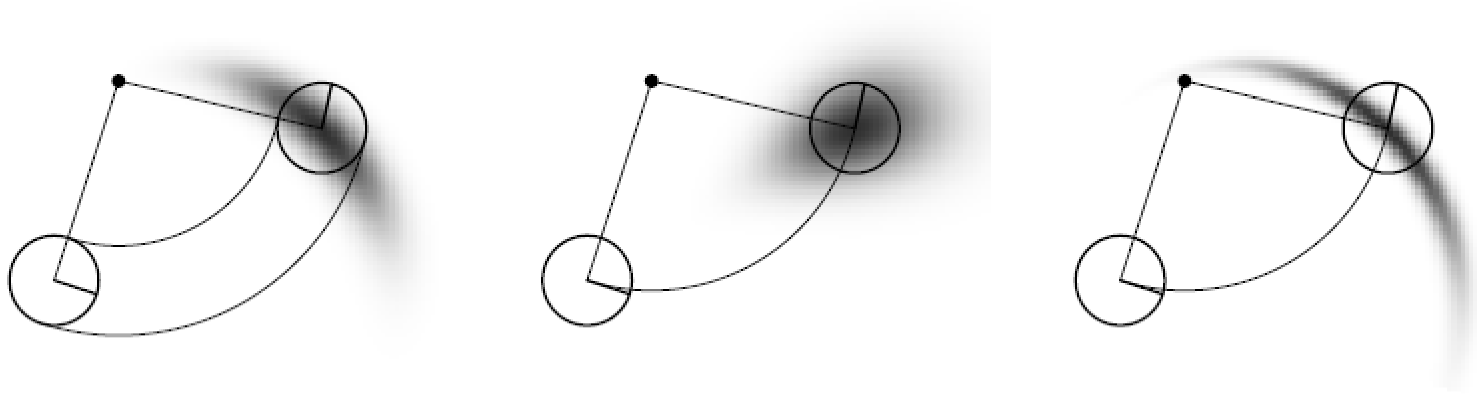
The “*motion model*”

Algorithm Markov_localization($bel(x_{t-1}), u_t, z_t, m$):
    for all x_t do
        $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}, m)\, bel(x_{t-1})\, dx$
        $bel(x_t) = \eta\, p(z_t \mid x_t, m)\, \overline{bel}(x_t)$
    endfor
    return $bel(x_t)$

The “*sensor model*”

Up Next:

Probabilistic Models of Robot Motion



$$p(x_t \mid u_t, x_{t-1}, m)$$