

ME 598: Introduction to Robotics

Lecture 10: Localization, Path Planning, & Navigation

Stevens Institute of Technology
Dr. Mishah U. Salman
Fall 2013

Date:
By:

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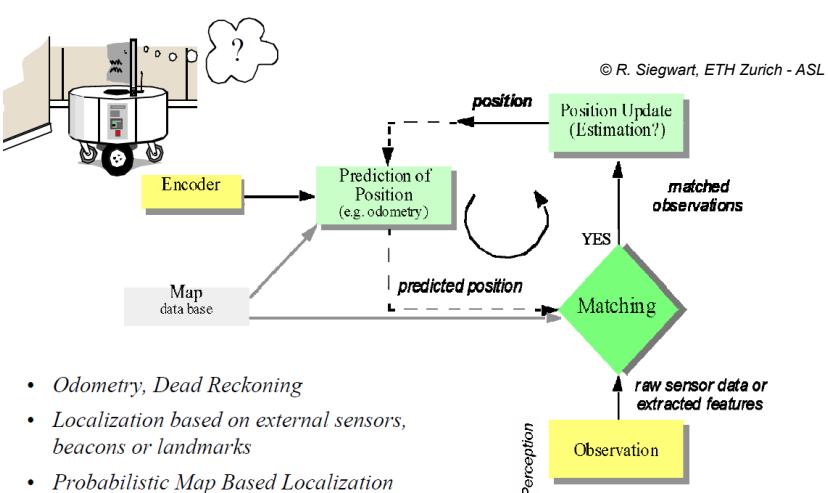
Localization, Path Planning, & Navigation

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Localization, Path Planning, & Navigation: Localization- Where am I?



```

graph TD
    Observation[Observation] -- "raw sensor data or extracted features" --> Matching{Matching}
    Matching -- YES --> PositionUpdate[Position Update  
(Estimation?)]
    PositionUpdate -- "position" --> Encoder[Encoder]
    Encoder --> Prediction[Prediction of Position  
(e.g. odometry)]
    Prediction -- "predicted position" --> Matching
    MapDatabase[Map data base] --> Prediction
    PositionUpdate -- "matched observations" --> PositionUpdate
  
```

- Odometry, Dead Reckoning
- Localization based on external sensors, beacons or landmarks
- Probabilistic Map Based Localization

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Localization, Path Planning, & Navigation: Localization- Challenges

- Knowing the absolute position (e.g. GPS) is not sufficient
- Localization in human-scale in relation with environment
- Planning in the *Cognition* step requires more than only position as input
- Perception and motion plays an important role
 - Sensor noise
 - Sensor aliasing
 - Effector noise
 - Odometric position estimation

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Localization, Path Planning, & Navigation: Sensor Noise

- Sensor noise is mainly influenced by environment
e.g. surface, illumination ...
- or by the measurement principle itself
e.g. interference between ultrasonic sensors
- Sensor noise drastically reduces the useful information of sensor readings.
The solution is:
 - to take multiple readings into account
 - employ temporal and/or multi-sensor fusion

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Localization, Path Planning, & Navigation: Effector Noise- Odometry, Deduced Reckoning

- Odometry and dead reckoning:
Position update is based on proprioceptive sensors
 - Odometry: wheel sensors only
 - Dead reckoning: also heading sensors
- The movement of the robot, sensed with wheel encoders and/or heading sensors is integrated to the position.
 - Pros: Straight forward, easy
 - Cons: Errors are integrated -> unbound
- Using additional heading sensors (e.g. gyroscope) might help to reduce the cumulated errors, but the main problems remain the same.

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Localization, Path Planning, & Navigation: Sensor Aliasing

- In robots, non-uniqueness of sensors readings is the norm
- Even with multiple sensors, there is a many-to-one mapping from environmental states to robot's perceptual inputs
- Therefore the amount of information perceived by the sensors is generally insufficient to identify the robot's position from a single reading
 - Robot's localization is usually based on a series of readings
 - Sufficient information is recovered by the robot over time

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Localization, Path Planning, & Navigation: Odometry- Error Sources

- deterministic (systematic) non-deterministic (non-systematic)
- deterministic errors can be eliminated by proper calibration of the system.
 - non-deterministic errors have to be described by error models and will always lead to uncertain position estimate.
- Major Error Sources:
- Limited resolution during integration (time increments, measurement resolution)
 - Misalignment of the wheels (deterministic)
 - Unequal wheel diameter (deterministic)
 - Variation in the contact point of the wheel
 - Unequal floor contact (slipping, not planar ...)

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Localization, Path Planning, & Navigation: Odometry- Classification of Integration Errors

- Range error: integrated path length (distance) of the robots movement
 - sum of the wheel movements
- Turn error: similar to range error, but for turns
 - difference of the wheel motions
- Drift error: difference in the error of the wheels leads to an error in the robots angular orientation
- Over long periods of time, turn and drift errors far outweigh range errors!
 - Consider moving forward on a straight line along the x axis. The error in the y-position introduced by a move of d meters will have a component of $d\sin Dq$, which can be quite large as the angular error Dq grows.

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Localization, Path Planning, & Navigation: Odometry- Differential Drive Robot

Kinematics

$$\Delta x = \Delta s \cos(\theta + \Delta\theta/2)$$

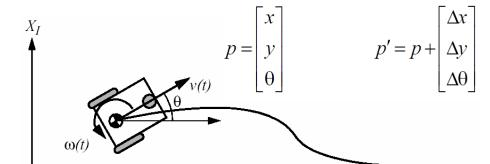
$$\Delta y = \Delta s \sin(\theta + \Delta\theta/2)$$

$$\Delta\theta = \frac{\Delta s_r - \Delta s_l}{b}$$

$$\Delta s = \frac{\Delta s_r + \Delta s_l}{2}$$

$$p' = f(x, y, \theta, \Delta s_r, \Delta s_l) = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} \cos\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r + \Delta s_l}{2} \sin\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix}$$

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$\Delta s_r, \Delta s_l$ = traveled distances for right and left wheel
 b = distance between two wheels on robot

$$p' = f(x, y, \theta, \Delta s_r, \Delta s_l) = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2} \cos\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r + \Delta s_l}{2} \sin\left(\theta + \frac{\Delta s_r - \Delta s_l}{2b}\right) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix}$$

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Localization, Path Planning, & Navigation: Odometry- Differential Drive Robot

Error model

- Assumptions:

- Errors of individual wheels are independent
- Variance of wheel errors are proportional to absolute value of traveled distance

$$\Sigma_{\Delta} = covar(\Delta s_r, \Delta s_l) = \begin{bmatrix} k_r |\Delta s_r| & 0 \\ 0 & k_l |\Delta s_l| \end{bmatrix}$$

(Sections 4.2 and 5.2.4)

Known initial conditions

$$\Sigma_{p'} = \nabla_{p'} f \cdot \Sigma_p \cdot \nabla_{p'} f^T + \nabla_{\Delta_H} f \cdot \Sigma_{\Delta} \cdot \nabla_{\Delta_H} f^T$$

$$F_p = \nabla_p f = \nabla_p(f^T) = \begin{bmatrix} \frac{\partial f}{\partial x} \frac{\partial f}{\partial y} \frac{\partial f}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta s \sin(\theta + \Delta\theta/2) \\ 0 & 1 & \Delta s \cos(\theta + \Delta\theta/2) \\ 0 & 0 & 1 \end{bmatrix}$$

$$F_{\Delta_H} = \begin{bmatrix} \frac{1}{2} \cos\left(\theta + \frac{\Delta\theta}{2}\right) - \frac{\Delta s}{2} \sin\left(\theta + \frac{\Delta\theta}{2}\right) & \frac{1}{2} \cos\left(\theta + \frac{\Delta\theta}{2}\right) + \frac{\Delta s}{2} \sin\left(\theta + \frac{\Delta\theta}{2}\right) \\ \frac{1}{2} \sin\left(\theta + \frac{\Delta\theta}{2}\right) + \frac{\Delta s}{2b} \cos\left(\theta + \frac{\Delta\theta}{2}\right) & \frac{1}{2} \sin\left(\theta + \frac{\Delta\theta}{2}\right) - \frac{\Delta s}{2b} \cos\left(\theta + \frac{\Delta\theta}{2}\right) \\ \frac{1}{b} & -\frac{1}{b} \end{bmatrix}$$

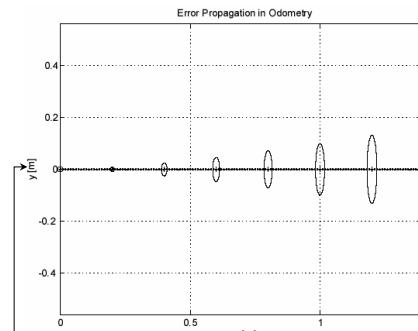
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Localization, Path Planning, & Navigation: Odometry- Growth of Pose Uncertainty

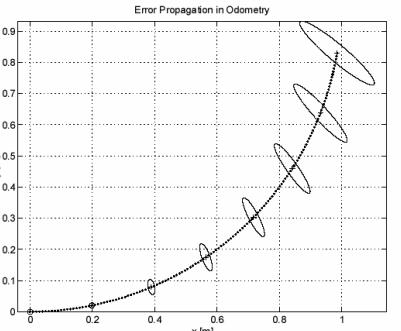
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Straight Line Movement



- Errors perpendicular to the direction of movement grow much more quickly
- Error ellipses do not remain perpendicular to the direction of movement

Movement on a Circle

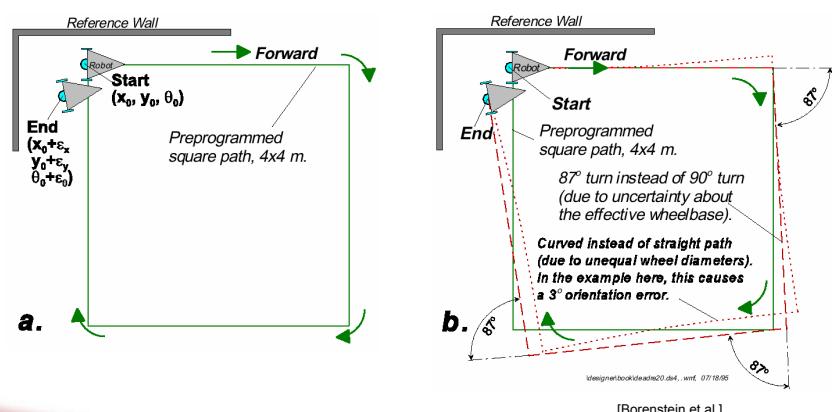


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Localization, Path Planning, & Navigation: Odometry- Calibration of Errors

- Unidirectional square path experiment

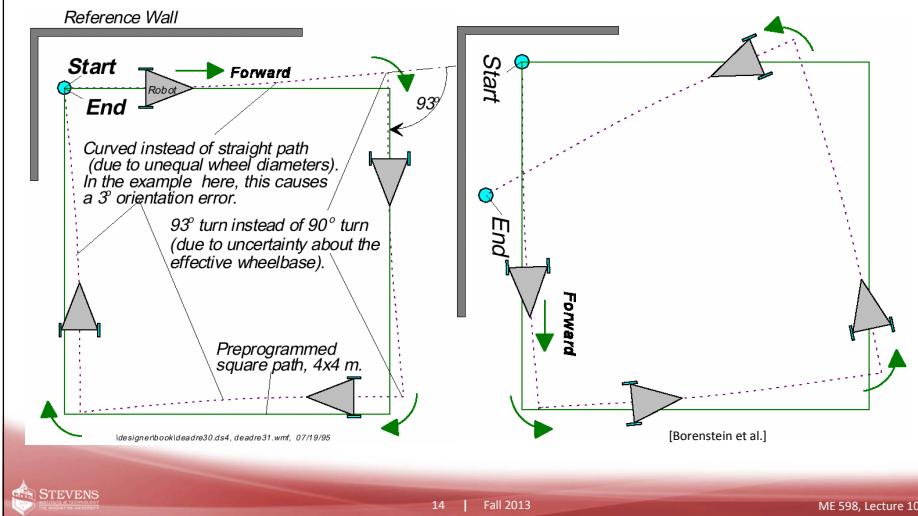


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Localization, Path Planning, & Navigation: Odometry- Calibration of Errors

- Bi-directional square path experiment



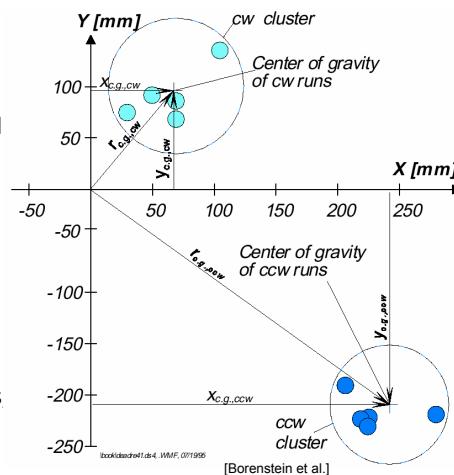
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Localization, Path Planning, & Navigation: Odometry- Calibration of Errors

- Deterministic errors (systematic)
 - From wheels diameters, wheel base, misalignment, encoder errors, etc.

$$E_{\text{systematic}} = \max(r_{c.g.,cw}; r_{c.g.,ccw})$$



- Non-deterministic errors (non-systematic)
 - From travel over uneven floors objects, wheel slippage, etc.

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Localization, Path Planning, & Navigation: To Localize or Not?

- How to navigate between A and B
 - navigation without hitting obstacles
 - detection of goal location

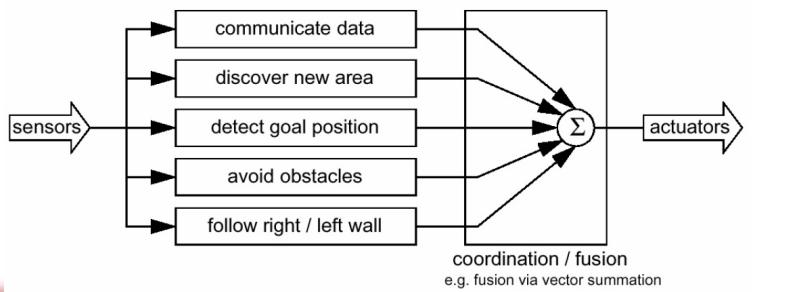


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Localization, Path Planning, & Navigation: Behavior (Sensor) Based Navigation

- Procedural solution to navigation problem
 - Simple and Quick implementation (+)
 - Doesn't translate/scale well to other environments (-)
 - Underlying procedures can be complicated (-)
 - Running multiple behaviors at once requires fine tuning (-)

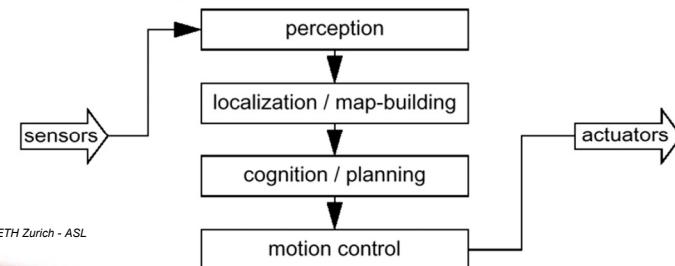


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Localization, Path Planning, & Navigation: Model (Map) Based Navigation

- Robot explicitly attempts to localize by collecting sensor data and updates belief about position wrt a map
 - Requires more upfront effort (-)
 - Architecture can be leveraged to map and navigate a variety of environments (+)
 - Behavior only as good as map (-)



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Localization, Path Planning, & Navigation: Probabilistic, Map-Based Localization

- Consider a mobile robot moving in a known environment.
- As it starts to move, say from a precisely known location, it might keep track of its location using **odometry**.
- However, after a certain movement the robot will get very uncertain about its position.
→ update using an observation of its environment.
- Observation leads also to an estimate of the robot's position which can then be fused with the odometric estimation to get the best possible update of the robot's actual position.

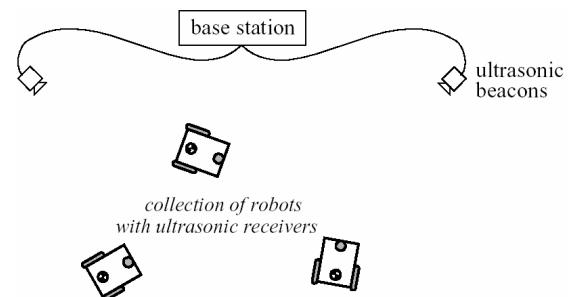
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Localization, Path Planning, & Navigation: Positioning Beacon Systems- Triangulation

- Robot knows positions of beacons in global reference frame
- Localizes own position in frame through triangulation, i.e. geometry



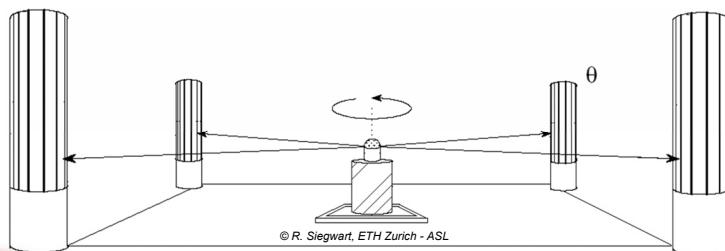
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Localization, Path Planning, & Navigation: Positioning Beacon Systems- Triangulation

- Industrial setting example:

- Beacons are retroreflective markers that reflect energy back to robot
- Known positions for optical retroreflectors
- Need 3 beacons in sight to determine position
 - High reliability
 - Costly setup, only works in that particular environment



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Localization, Path Planning, & Navigation: SLAM: Simultaneous Localization and Mapping

- Goal:

- Start robot from an arbitrary initial point
- Autonomous exploration of environment with on-board sensors
- Acquire knowledge about environment
- Interpret the scene and build an appropriate map
- Localize itself relative to this map



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Localization, Path Planning, & Navigation: Competencies for Navigation

- Cognition / Reasoning :

- is the ability to decide **what actions are required** to achieve a **certain goal** in a **given situation (belief state)**.
- decisions ranging from **what path to take** to what **information on the environment to use**.
- Today's **industrial robots** can operate without any cognition (reasoning) because their environment is **static** and very **structured**.
- In mobile robotics, **cognition and reasoning** is primarily of **geometric nature**, such as picking safe path or determining where to go next.
 - already been largely explored in literature for cases in which complete information about the current situation and the environment exists (e.g. sales man problem).

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Localization, Path Planning, & Navigation: Competencies for Navigation

- However, in mobile robotics the **knowledge** of about the environment and situation is usually **only partially known** and is **uncertain**.

- makes the task much more difficult
- requires **multiple tasks running in parallel**, some for planning (global), some to guarantee "survival of the robot".

- Robot control can usually be **decomposed** in various behaviors or functions
 - e.g. wall following, localization, path generation or obstacle avoidance.
- In chapter 6 we are concerned with **path planning** and **navigation**

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Localization, Path Planning, & Navigation: Path Planning

- The problem: find a path in the physical space from the initial position to the goal position avoiding all collisions with the obstacles
- We can generally distinguish between
 - (global) path planning and
 - (local) obstacle avoidance.

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Localization, Path Planning, & Navigation: Global Path Planning

- Assumption: there exists a good enough map of the environment for navigation.
 - Topological or metric or a mixture between both.
- First step:
 - Representation of the environment by a road-map (graph), cells or a potential field. The resulting discrete locations or cells allow then to use standard planning algorithms.
- Examples that we will see:
 - Visibility Graph
 - Voronoi Diagram
 - Cell Decomposition -> Connectivity Graph
 - Potential Field

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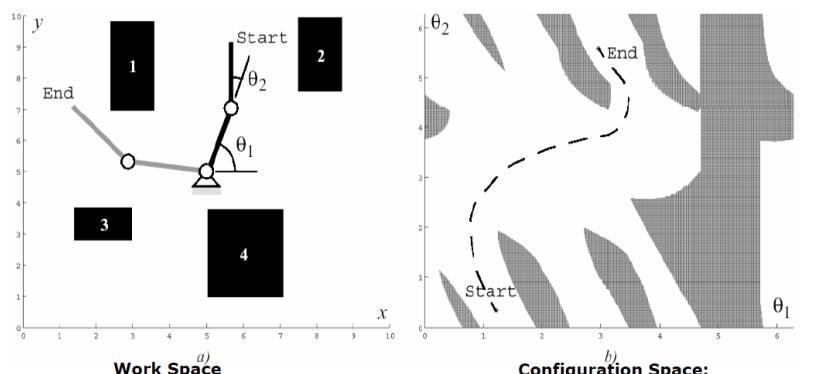


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Localization, Path Planning, & Navigation: Path Planning- Configuration Space

- State or configuration q can be described with k values q_i



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Localization, Path Planning, & Navigation: Configuration Space- Mobile Robot

- Mobile robots operating on a flat ground have 3 DoF: (x, y, θ)
- For simplification, mobile roboticists assume that the robot is a point. In this way the configuration space is reduced to 2D (x, y)
- Because we have reduced each robot to a point, we have to inflate each obstacle by the size of the robot radius to compensate.

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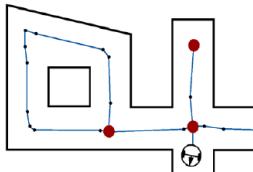
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Localization, Path Planning, & Navigation: Path Planning Overview

1. Road Map, Graph construction

- Identify a set of routes within the free space



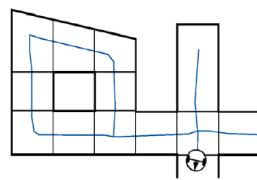
- Where to put the nodes?

- Topology-based:
 - at distinctive locations
- Metric-based:
 - where features disappear or get visible



2. Cell decomposition

- Discriminate between free and occupied cells



- Where to put the cell boundaries?

- Topology- and metric-based:
 - where features disappear or get visible
- Imposing a mathematical function over the space

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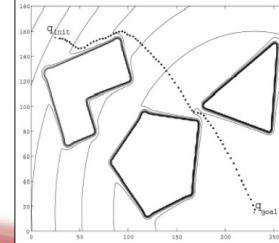
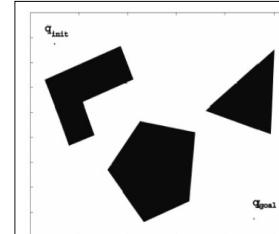
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Localization, Path Planning, & Navigation: Potential Field Path Planning

- Robot is treated as a *point under the influence* of an artificial potential field.

- Generated robot movement is similar to ball rolling down the hill
- Goal generates attractive force
- Obstacles are repulsive forces

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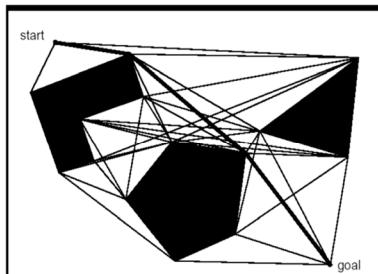
Localization, Path Planning, & Navigation: Road-Map Path Planning- Visibility Graph

Nodes of graph:

- initial and goal positions
- vertices of obstacles

Road map:

- All nodes visible from each other connected by straight-line segments to define map



Pros

- It is easy to find the shortest path from the start to the goal positions
- Implementation simple when obstacles are polygons

Cons

- Number of edges and nodes increases with the number of polygons
- Thus it can be inefficient in densely populated environments
- The solution path found by the visibility graph tends to take the robot as close as possible to obstacles: the common solution is to grow obstacles by more than robot's radius

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Localization, Path Planning, & Navigation: Road-Map Path Planning- Voronoi Diagram

- Lines constructed from points that are equidistant from two or more obstacles

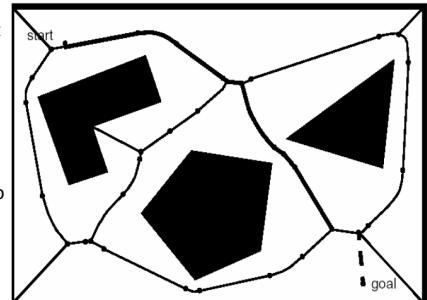
- Maximizes distance between robot and obstacles

- Initial and goal states mapped to diagram by drawing line to edge along which its distance to the boundary of the obstacle increases the fastest

- Direction of movement selected so the distance to the boundaries increases fastest

- Easy to execute: maximize sensor readings

- Works for map-building: move on Voronoi edges



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Pros

- Using range sensors like laser or sonar, a robot can navigate along the Voronoi diagram using simple control rules

Cons

- Because the Voronoi diagram tends to keep the robot as far as possible from obstacles, any short range sensor will be in danger of failing

Peculiarities

- when obstacles are polygons, the Voronoi map consists of straight and parabolic segments

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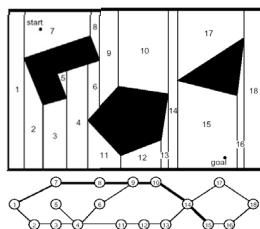
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Localization, Path Planning, & Navigation: Road-Map Path Planning- Cell Decomposition

- Divide space into simple, connected regions called cells
- Determine which open cells are adjacent and construct a connectivity graph
- Find cells in which the initial and goal configuration (state) lie and search for a path in the connectivity graph to join them.
- From the sequence of cells found with an appropriate search algorithm, compute a path within each cell.
 - e.g. passing through the midpoints of cell boundaries or by sequence of wall following movements.
- Possible cell decompositions:
 - Exact cell decomposition
 - Approximate cell decomposition:
 - Fixed cell decomposition
 - Adaptive cell decomposition



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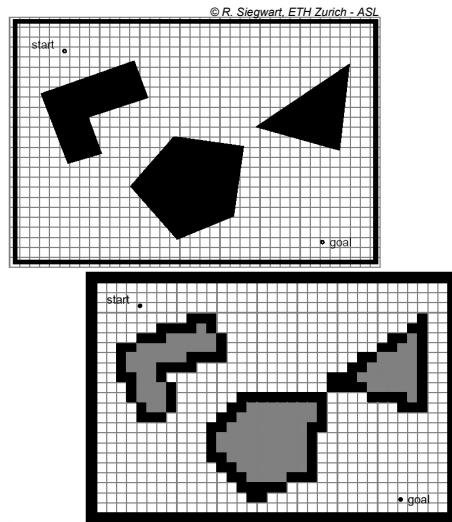
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Localization, Path Planning, & Navigation: Approximate Cell Decomposition- Grids

- Fixed grid-sized decomposition
- Cell size not dependant on particular objects in environment
- Cell is either free or obstacle-filled
- Low computational complexity for path planning (+)
- Fundamental cost is memory
 - Even sparse environment must be represented in its entirety (-)
- Narrow passageways can be lost (-)

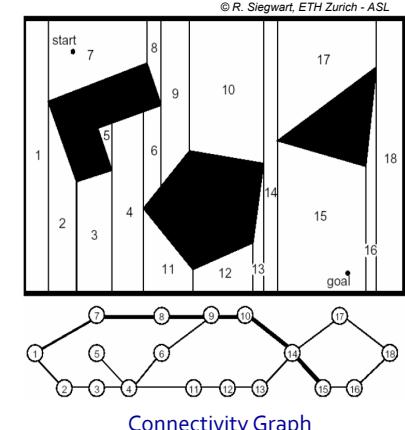


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Localization, Path Planning, & Navigation: Exact Cell Decomposition

- Boundary of cells based on critical geometry
- Cells are either completely free or completely occupied
- Robot position in free cell does not matter
- Robot ability to traverse from free cell to adjacent free cell matters
- # of cells and planning computation efficiency depends on density and complexity of obstacles in environment (-)
- In large sparse environments, very small # of cells and efficient (+)



Connectivity Graph

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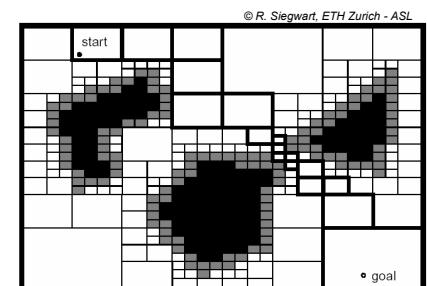
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Localization, Path Planning, & Navigation: Adaptive Cell Decomposition

- Free space externally bounded by rectangle and internally bounded by 3 polygons
- Recursively decompose rectangle into 4 smaller rectangles
- At each resolution, only cells whose interiors lie entirely in free space are used to construct connectivity graph
- Adapts to complexity of environment



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Localization, Path Planning, & Navigation: Path/Graph Search Strategies

- Wavefront Expansion
- Breadth-First Search
- Depth-First Search
- A*

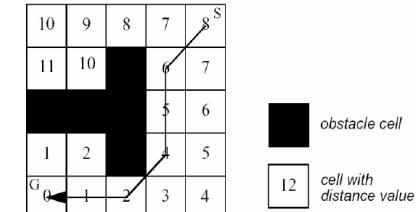


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Localization, Path Planning, & Navigation: Path/Graph Search Strategies

- Wavefront Expansion (grassfire)
 - Starting from goal position, mark each cell its distance to the to the goal cell
 - Continue until start position is reached
 - Estimate of robots distance to goal
 - Planner:
 - Links together cells that are adjacent and always closer to the goal = path



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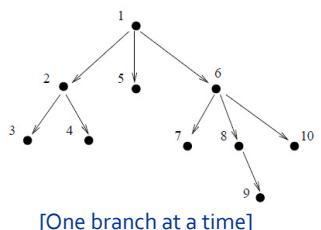


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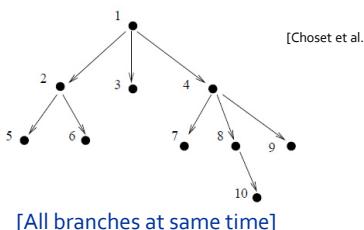
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Localization, Path Planning, & Navigation: Depth-First Search vs. Breadth-First Search

Depth-first search



Breadth-first search



- Numbers on each node reflect the order in which nodes are expanded in the search

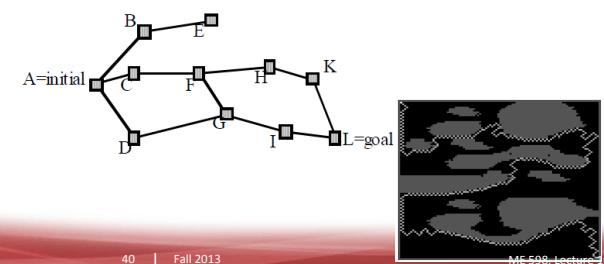
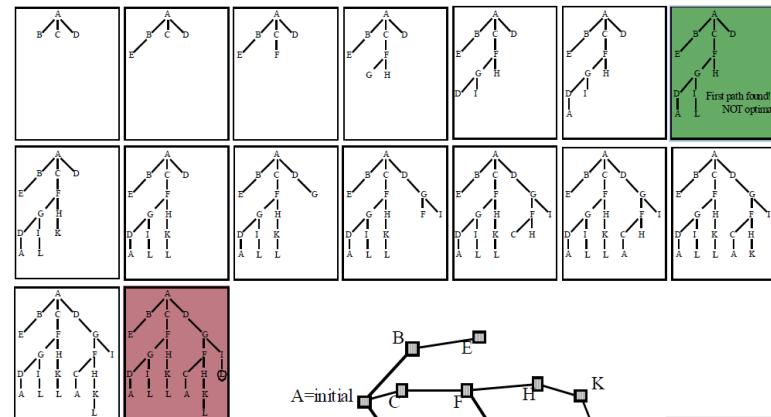


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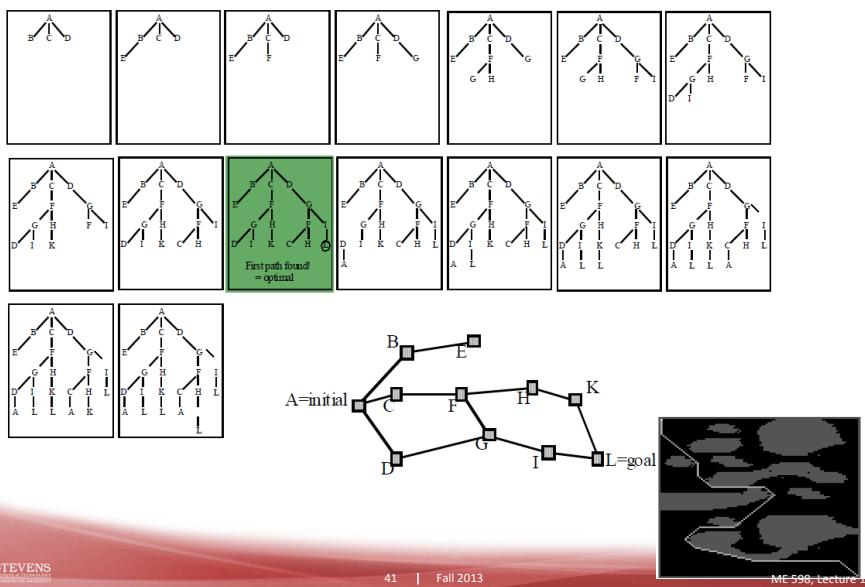
Localization, Path Planning, & Navigation: Depth-First Search

[Choset et al.]



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Localization, Path Planning, & Navigation: Breadth-First Search



Localization, Path Planning, & Navigation: Search Algorithms

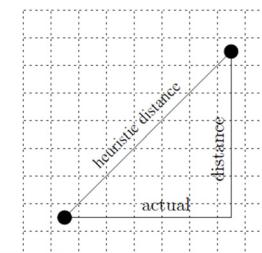
- Define a *heuristic*: an expected but not necessarily actual, cost to the goal node
- Example:
 - Search may choose explore next node that has shortest Euclidean distance to goal bc/ node has highest possibility (based on local info) of getting closest to goal
 - No guarantee that node will lead to (globally) shortest path in the graph to goal
 - Good guess, based on information that is available

Localization, Path Planning, & Navigation: Search Algorithms

- Depth-first: fastest solution to find a path
- Breadth-first: shortest path to start node in terms of link lengths
- Wavefront: shortest path with respect to Manhattan distance (graph with edge lengths = 1)
- Shortest-path length may not always be the only metric want to optimize
 - Energy, time, traversability, safety, etc.
- Minimize the # of nodes to be visited to locate the goal node subject to path optimality criteria
 - Optimality: measures path
 - Efficiency: measures the search (# of nodes visited to determine path)

Localization, Path Planning, & Navigation: A* Algorithm

- Searches a graph efficiently with respect to a chosen heuristic
 - “Good” heuristic, efficient search
 - “Bad” heuristic, path will be found, inefficient search, suboptimal path
 - “Optimistic” heuristic will return an optimal path
 - Heuristic always returns a value less than or equal to the cost of the shortest path from the current node to the goal node



Localization, Path Planning, & Navigation: A* on a Grid

- Start node is put on the priority queue, with $f = h$:

$h=6$	$h=3$	$h=2$	$h=1$	$h=0$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.4$	$h=3.4$	$h=2.4$	$h=1.4$	$h=1$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.8$	$h=3.8$	$h=2.8$	$h=2.4$	$h=2$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.2$	$h=4.2$	$h=3.8$	$h=3.4$	$h=3$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.6$	$h=6.6$	$h=5.6$	$h=4.8$	$h=4.4$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=8.0$	$h=7.0$	$h=6.6$	$h=6.2$	$h=5.8$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$

[Choset et al.]

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Localization, Path Planning, & Navigation: A* on a Grid

- Expand cell with highest priority next (lowest f)

$h=6$	$h=3$	$h=2$	$h=1$	$h=0$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.4$	$h=3.4$	$h=2.4$	$h=1.4$	$h=1$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.8$	$h=3.8$	$h=2.8$	$h=2.4$	$h=2$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.2$	$h=4.2$	$h=3.8$	$h=3.4$	$h=3$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.6$	$h=6.6$	$h=5.6$	$h=4.8$	$h=4.4$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=8.0$	$h=7.0$	$h=6.6$	$h=6.2$	$h=5.8$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$

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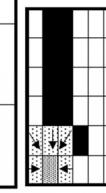
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Localization, Path Planning, & Navigation: A* on a Grid

- Expand the start node, update priority queue, set backpointers:

$h=6$	$h=3$	$h=2$	$h=1$	$h=0$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.4$	$h=3.4$	$h=2.4$	$h=1.4$	$h=1$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.8$	$h=3.8$	$h=2.8$	$h=2.4$	$h=2$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.2$	$h=4.2$	$h=3.8$	$h=3.4$	$h=3$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.6$	$h=6.6$	$h=5.6$	$h=4.8$	$h=4.4$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=8.0$	$h=7.0$	$h=6.6$	$h=6.2$	$h=5.8$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$

(3,2)	7.0	[Choset et al.]
(2,2)	7.6	
(3,1)	7.6	
(1,2)	9.0	
(1,1)	9.0	
State	f	



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Localization, Path Planning, & Navigation: A* on a Grid

- Continue until goal state gets expanded
- Since priority value of goal cell is lower than the priorities of all other cells in queue, the path is optimal, and A* terminates
- Trace the backpointers to find optimal path from start to goal

$h=6$	$h=3$	$h=2$	$h=1$	$h=0$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.4$	$h=3.4$	$h=2.4$	$h=1.4$	$h=1$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=6.8$	$h=3.8$	$h=2.8$	$h=2.4$	$h=2$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.2$	$h=4.2$	$h=3.8$	$h=3.4$	$h=3$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=7.6$	$h=6.6$	$h=5.6$	$h=4.8$	$h=4.4$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$
$h=8.0$	$h=7.0$	$h=6.6$	$h=6.2$	$h=5.8$
$f =$				
$b=()$	$b=()$	$b=()$	$b=()$	$b=()$

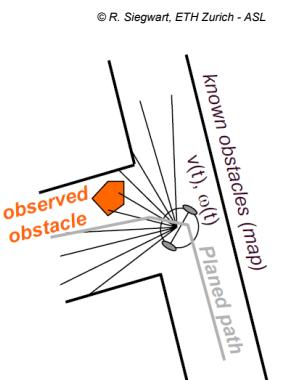
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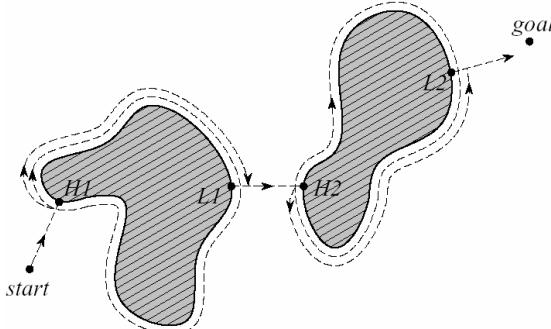
Localization, Path Planning, & Navigation: Obstacle Avoidance (Local Path Planning)

- The goal of the obstacle avoidance algorithms is to avoid collisions with obstacles
- It is usually based on local map
- Often implemented as a more or less independent task
- However, efficient obstacle avoidance should be optimal with respect to
 - the overall goal
 - the actual speed and kinematics of the robot
 - the on board sensors
 - the actual and future risk of collision



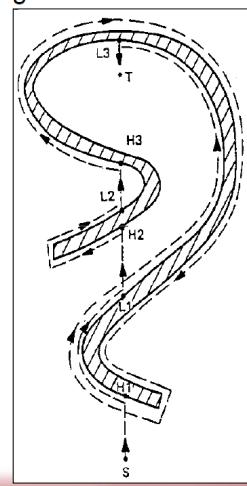
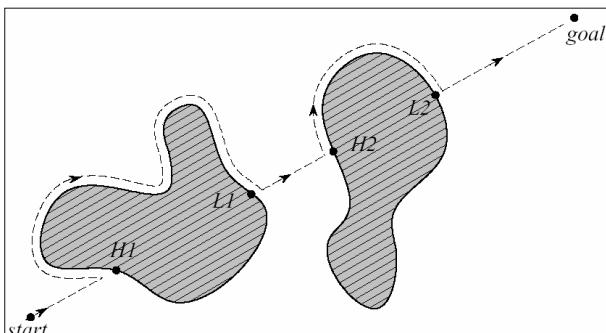
Localization, Path Planning, & Navigation: Obstacle Avoidance- Bug1 Algorithm

- Following along the obstacle to avoid it
- Each encountered obstacle is once fully circled before it is left at the point closest to the goal

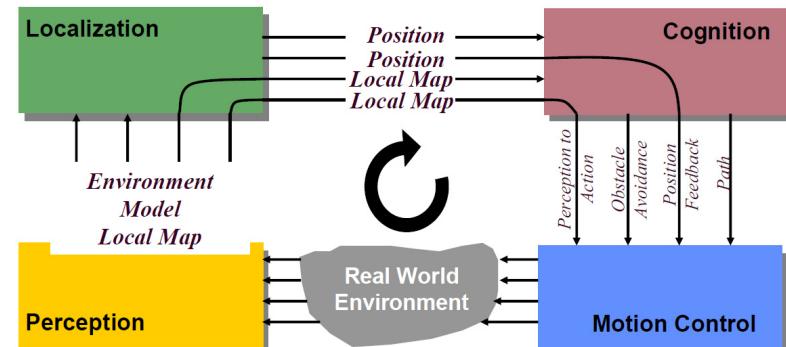


Localization, Path Planning, & Navigation: Obstacle Avoidance- Bug2 Algorithm

- Following the obstacle always on the left or right side
- Leaving the obstacle if the direct connection between start and goal is crossed

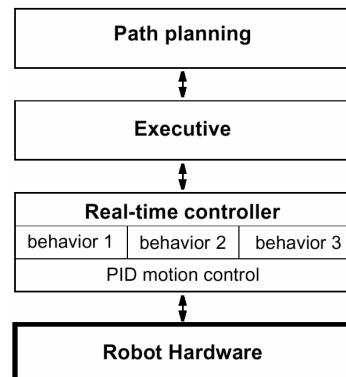


Localization, Path Planning, & Navigation: Mobile Robot General Architecture



Localization, Path Planning, & Navigation: Tiered Navigation Architecture

- Path Planning
 - Strategic level decision making
 - Uses global information (in non-real-time) to identify sequence of local actions for robot
- Real-time controller
 - Requires high-band width and tight sensor-effector loops
 - Includes lower level behaviors that may switch or run in parallel
- Executive
 - Responsible for mediating interface between planning and execution
 - Manages the activation of behaviors, failure recognition, and re-initiating planner



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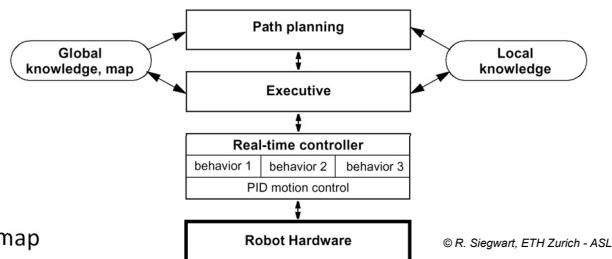
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Localization, Path Planning, & Navigation: Three-Tiered Episodic Planning Architecture

- Strategic, global map
- Short-term, local knowledge
- Executive decides when to trigger planner based on local information
 - Path blockage, failure, etc.
- Executive will then update global knowledge base accordingly



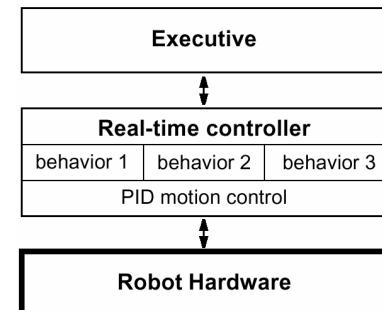
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Localization, Path Planning, & Navigation: Two-Tiered Architecture for Off-line Planning

- Executive must contain a priori all relevant schemes for traveling to desired destinations
- Not useful as general solution to navigation
- Good for static route-based applications
 - Factory or warehouse settings
 - Number of discrete goal positions small enough that executive can cache paths required to reach each goal rather than generic map which a planner could search for solution paths
- Good for extreme reliability demands
 - Can't afford a bad plan, compute it off-line ahead of time
 - Example: contingency flight plans for space shuttle in advance of shuttle flights



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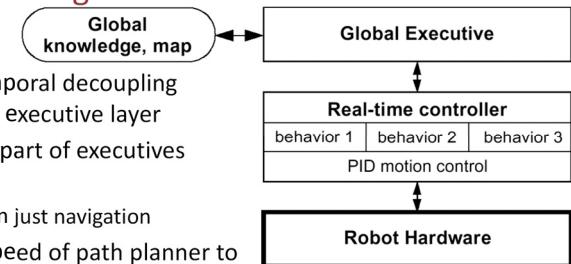
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Localization, Path Planning, & Navigation: Integrated Planning and Execution Architecture

- All integrated, no temporal decoupling between planner and executive layer
- Planning is one small part of executives cycle of activities
 - More functions than just navigation
- Requires execution speed of path planner to run within basic control loop of executive
 - Very computationally challenging
 - Example:
 - large off-road vehicle traveling over partially known terrains at high speeds
 - Local and global representations are the same
 - Not possible in complex environments with current processor speeds



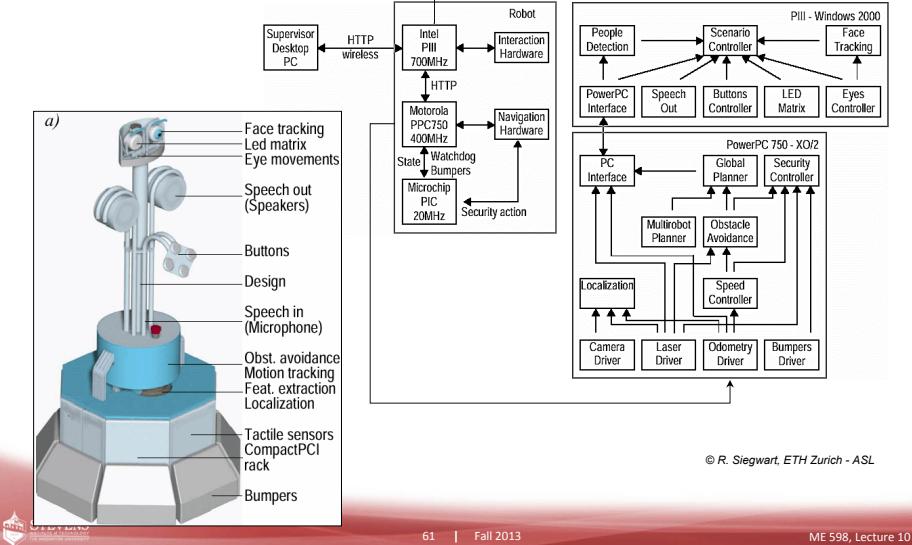
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Localization, Path Planning, & Navigation: Example- The RoboX Architecture



Localization, Path Planning, & Navigation: Extra References

- J. Borenstein, H. Everett, L. Feng, *Where am I? Sensors and Methods for Mobile Robot Positioning*. Ann Arbor, University of Michigan, 1996. Available at <http://www-personal.umich.edu/~johannb/shared/pos96rep.pdf>
- H. Choset, K. Lynch, S. Hutchinson, G. Kantor, W. Burgard, L. Kavraki, and S. Thrun, *Principles of Robot Motion: Theory, Algorithms, and Implementation*, MIT Press, Boston, 2005
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