上海科技大学
ShanghaiTech University

CS289: **Mobile Manipulation Fall 2024**

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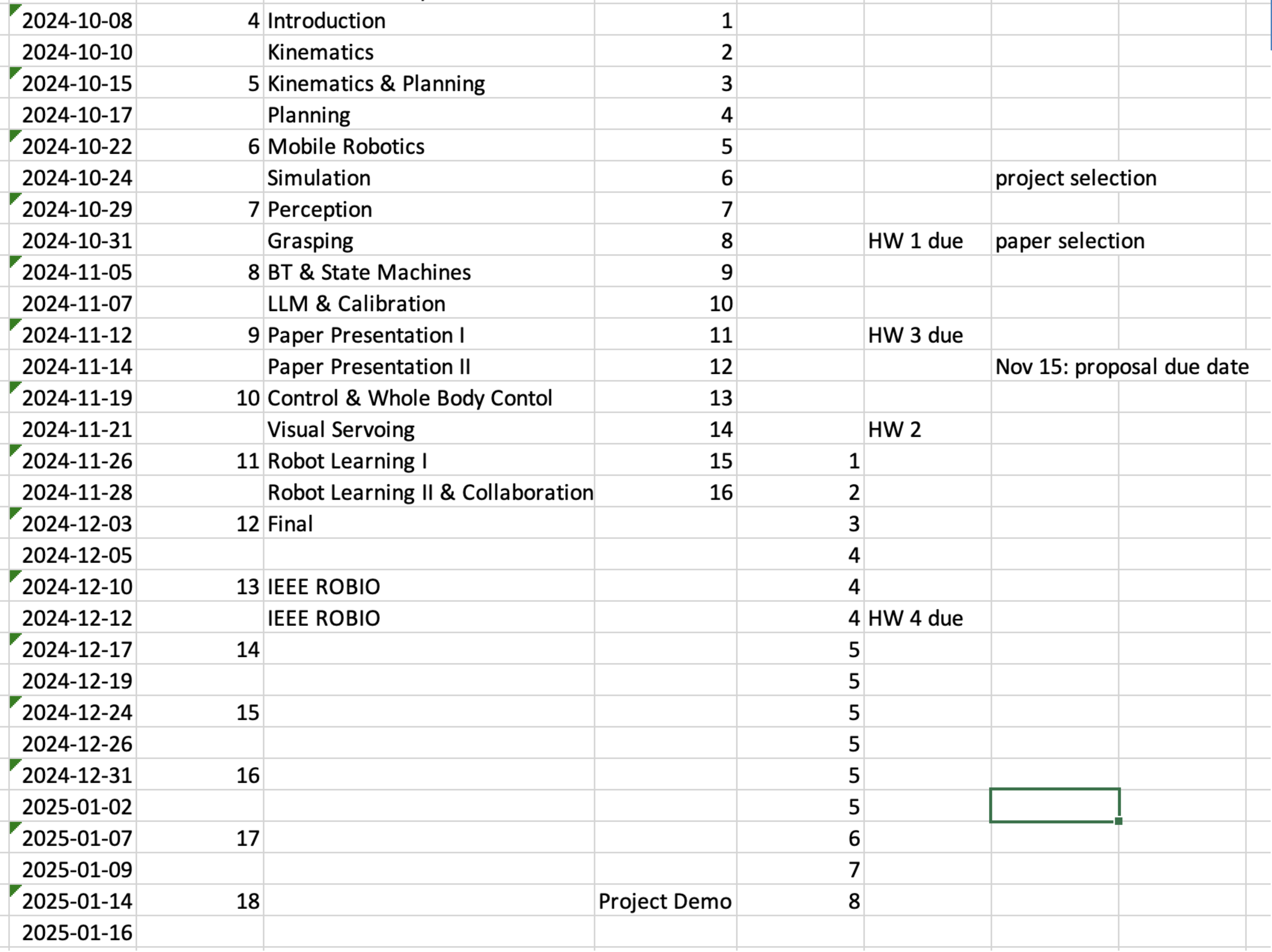
ShanghaiTech University

ADMIN

- Updated Schedule



2024-10-08	4	Introduction	1			
2024-10-10		Kinematics	2			
2024-10-15	5	Kinematics & Planning	3			
2024-10-17		Planning	4			
2024-10-22	6	Mobile Robotics	5			
2024-10-24		Simulation	6			project selection
2024-10-29	7	Perception	7			
2024-10-31		Grasping	8		HW 1 due	paper selection
2024-11-05	8	BT & State Machines	9			
2024-11-07		LLM & Calibration	10			
2024-11-12	9	Paper Presentation I	11		HW 3 due	
2024-11-14		Paper Presentation II	12			Nov 15: proposal due date
2024-11-19	10	Control & Whole Body Contol	13			
2024-11-21		Visual Servoing	14		HW 2	
2024-11-26	11	Robot Learning I	15	1		
2024-11-28		Robot Learning II & Collaboration	16	2		
2024-12-03	12	Final		3		
2024-12-05				4		
2024-12-10	13	IEEE ROBIO		4		
2024-12-12		IEEE ROBIO		4	HW 4 due	
2024-12-17	14			5		
2024-12-19				5		
2024-12-24	15			5		
2024-12-26				5		
2024-12-31	16			5		
2025-01-02				5		
2025-01-07	17			6		
2025-01-09				7		
2025-01-14	18		Project Demo	8		
2025-01-16						

HW

- HW1 is published
  - Gitlab accounts will be created soon (after project selection is done)
- HW2 will be published soon, too
  - A little bit interleaved with HW1 (a little overlap time-wise)
- HW3: paper presentation
- HW4: mission planning

Project Selection

- Topic selection: due this Thursday!
  - One member writes an email for the whole group to TA Jiajie: zhangjj2023@shanghaitech.edu.cn
  - Put the other group members on CC
  - Subject: [MoMa] Group Selection

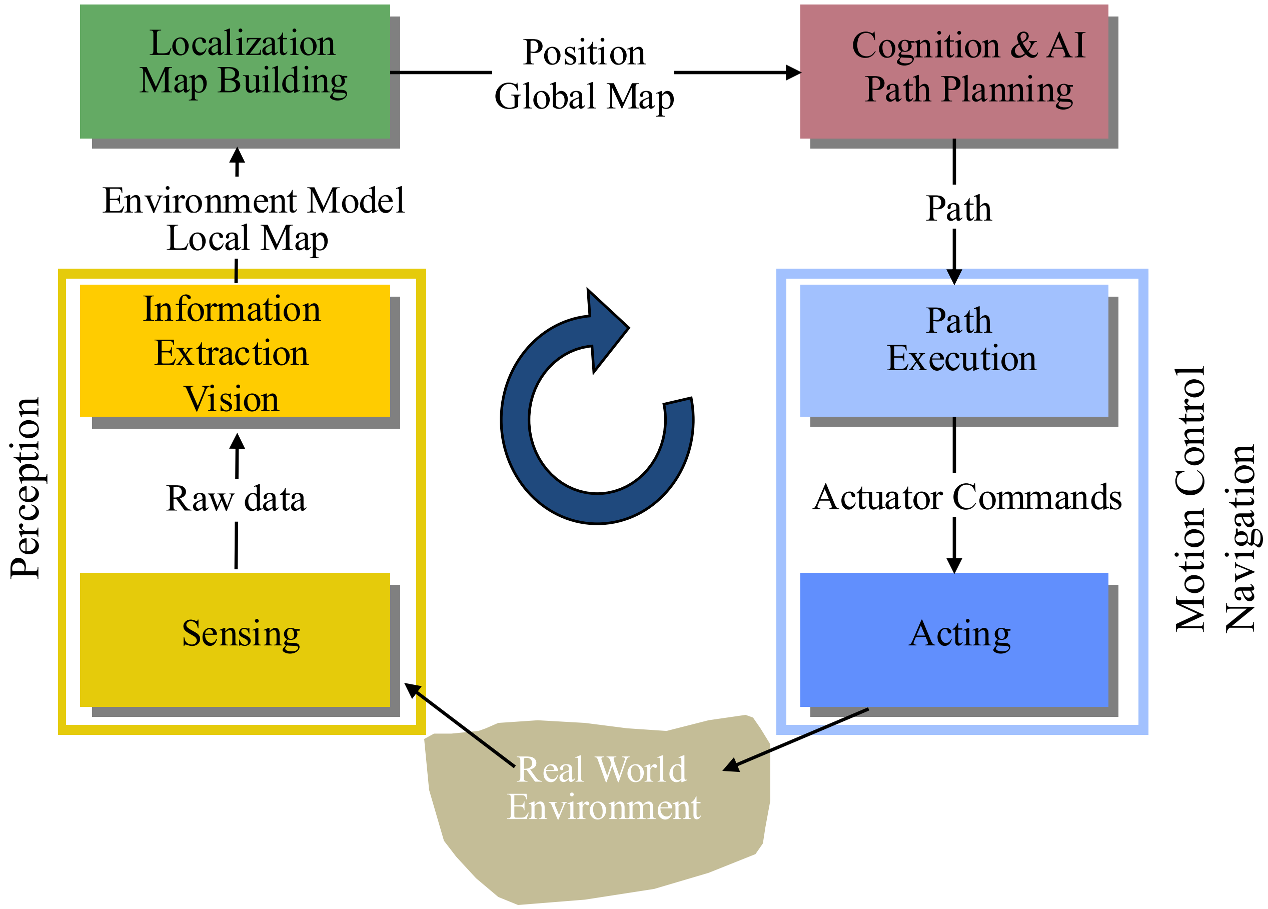
Paper Presentation Selection

- Paper selection: due Thursday, Oct 31!
  - Write email to TA Jiajie: zhangjj2023@shanghaitech.edu.cn
  - Subject: [MoMa] Paper Selection
  - If you don’t hear back, everything is OK
  - Otherwise Jiajie will let you know that your paper was taken already – you would need to select a different paper…

Outline: The “mobile” part of mobile manipulation

- General Control Scheme for mobile robotics
- Maps & Mapping
- SLAM
- Path Planning

General Control Scheme for Mobile Robot Systems



With material from Roland Siegwart and Davide Scaramuzza, ETH Zurich

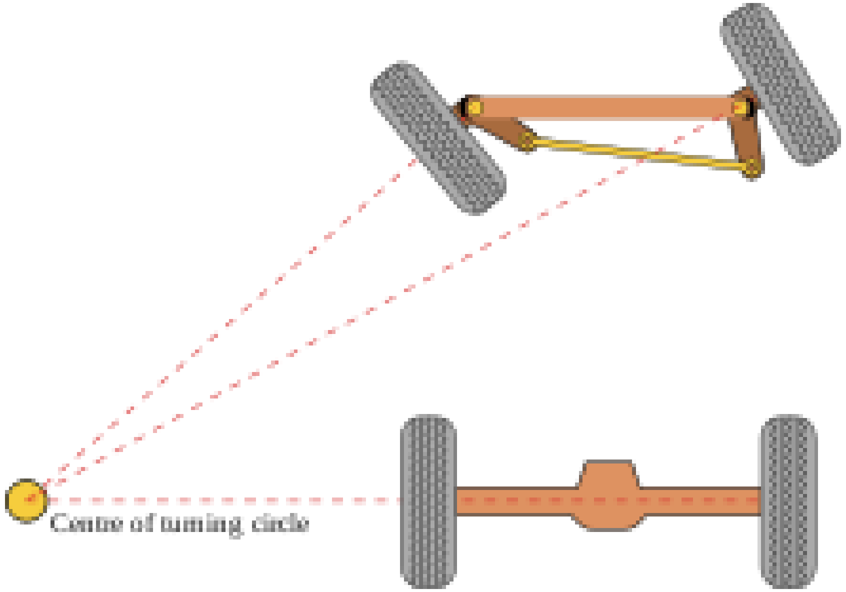
Mobile Robot Kinematics

- Aim
  - Description of mechanical behavior of the robot for *design* and *control*
  - Similar to robot manipulator kinematics
  - However, mobile robots can move unbound with respect to its environment
    - there is no direct way to measure the robot’s position
    - Position must be integrated over time
    - Leads to inaccuracies of the position (motion) estimate
      -> the number 1 challenge in mobile robotics

Differential Drive Robots

Ackermann Robot

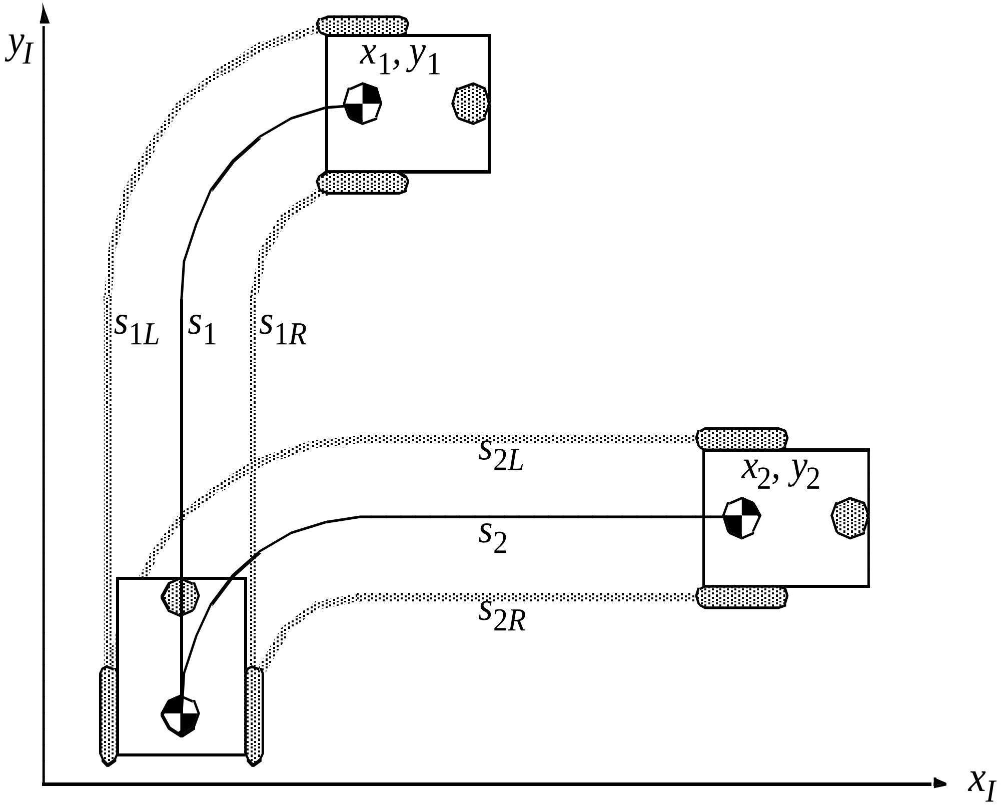
- No sideways slip than differential drive during turning ☺
- Cannot turn on the spot ☹



Mobile Robot Kinematics: Non-Holonomic Systems

$s_1 = s_2$; $s_{1R} = s_{2R}$; $s_{1L} = s_{2L}$

but: $x_1 \neq x_2$; $y_1 \neq y_2$

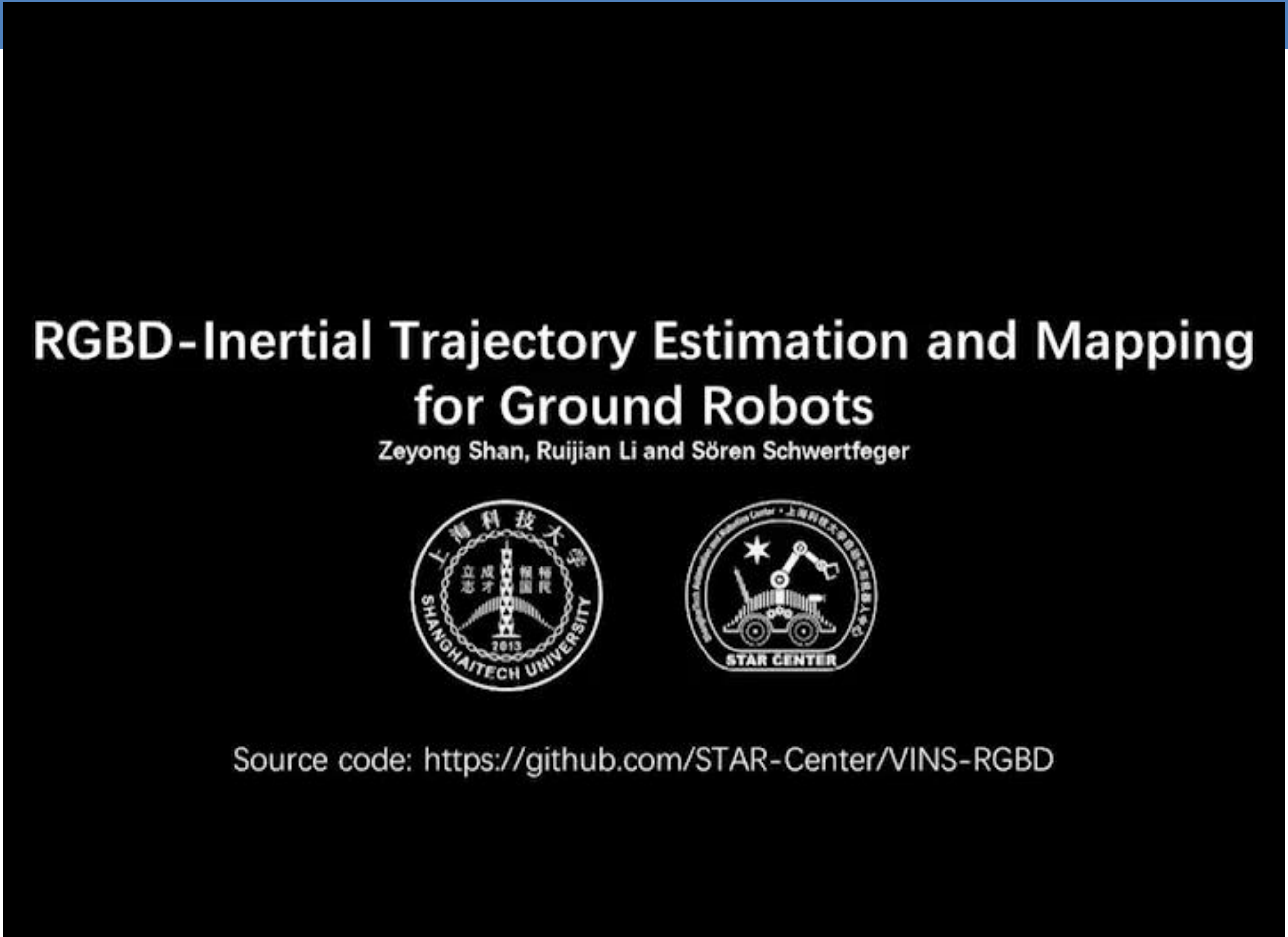


- Non-holonomic systems
  - differential equations are not integrable to the final pose.
  - the measure of the traveled distance of each wheel is not sufficient to calculate the final position of the robot. One has also to know how this movement was executed as a function of time.

MAPS & MAPPING

Map Representation: what is “saved” in the map

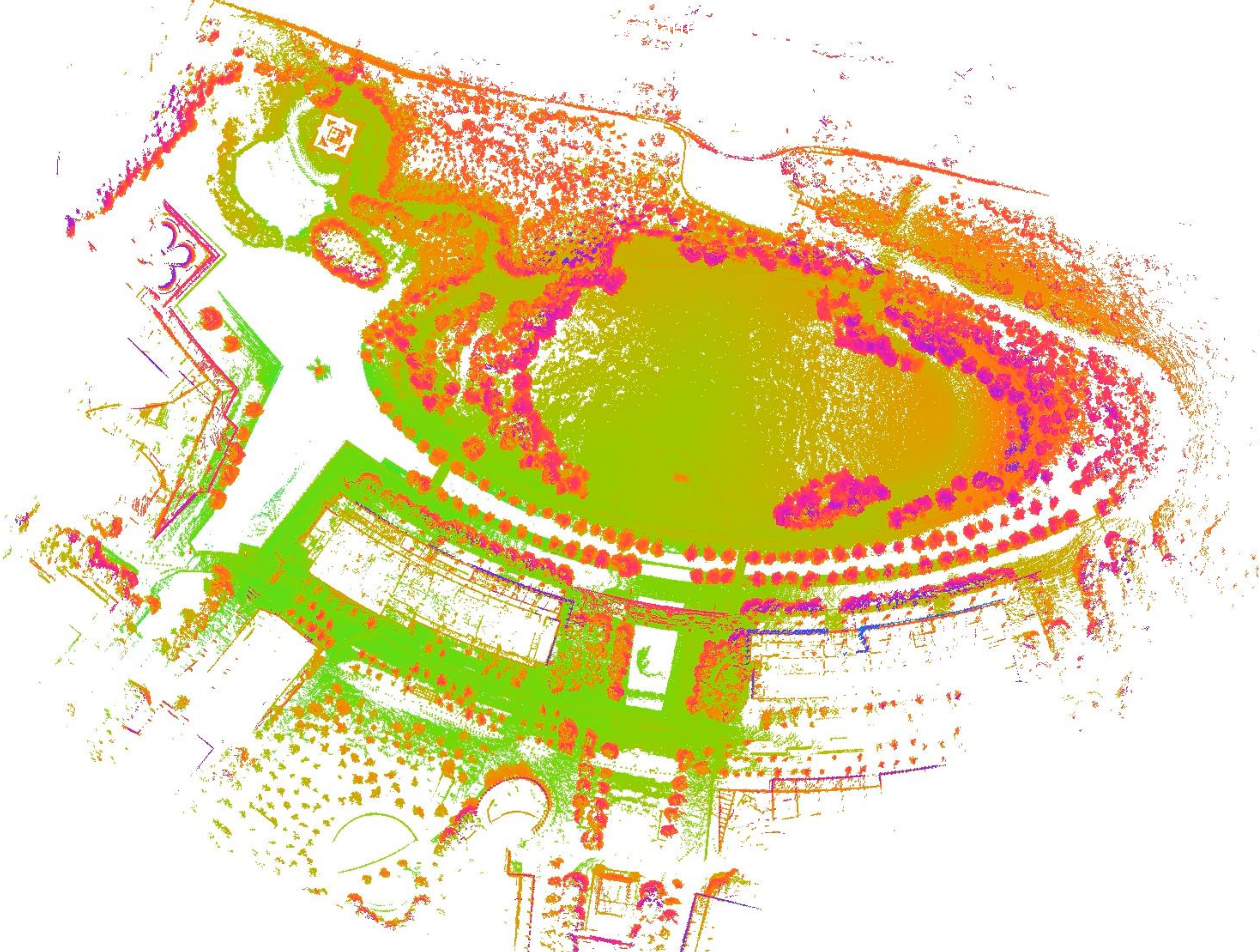
- Points (surface of objects, buildings): 2D or 3D
  - What: x,y or x,y,z coordinates;
    Optional: intensity; maybe RGB; maybe descriptor; temperature; …
  - From range sensors (laser, ultrasound, stereo, RGB-D): dense
  - From cameras (structure from motion; feature points): sparse
  - Variant: kd-tree
- Grid-map: 2D or 3D
  - Option: probabilistic grid map
  - Option: elevation map
  - Option: cost map
  - Option: Truncated Signed Distance Field
  - Option: Normal Distributions Transform (NDT)
  - Variant: Quad-tree; Oct-tree
- Higher-level Abstractions
  - Lines; Planes; Mesh
  - Curved: splines; Superquadrics
- Semantic Map
  - Assign semantic meaning to entities of a map representation from above
  - E.g. wall, ceiling, door, furniture, car, human, tree, …
- Topologic Map
  - High-level abstraction: places and connections between them
- Hierarchical Map
  - Combine Maps of different scales. E.g.:
  - Campus, building, floor
- Pose-Graph Based Map
  - Save (raw) sensor data in graph, annotated with the poses; generate maps on the fly
- Dynamic Map
  - Capture changing environment
- Hybrid Map
  - Combination of the above



RGBD-Inertial Trajectory Estimation and Mapping for Ground Robots

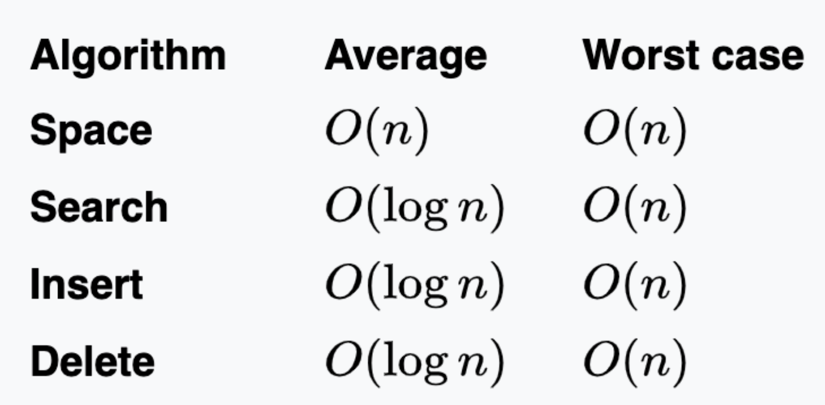
Zeyong Shan, Ruijian Li and Sören Schwertfeger

Source code: https://github.com/STAR-Center/VINS-RGBD

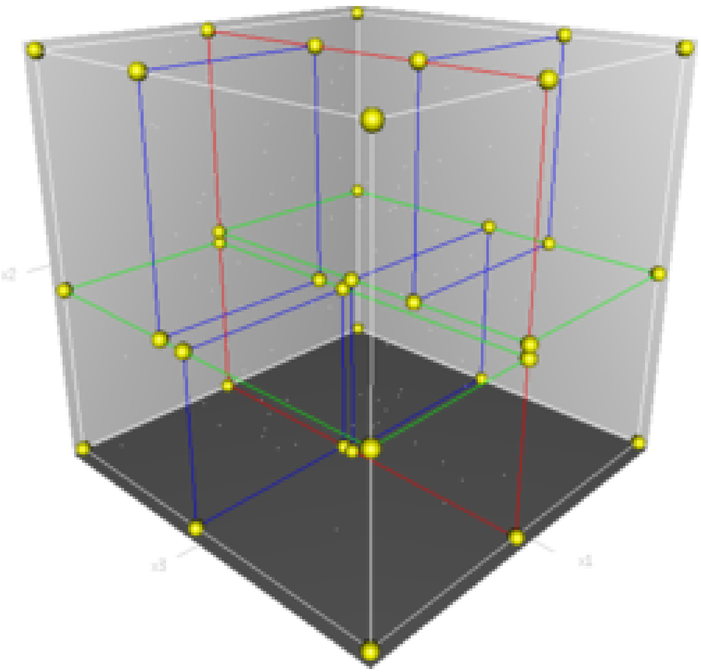


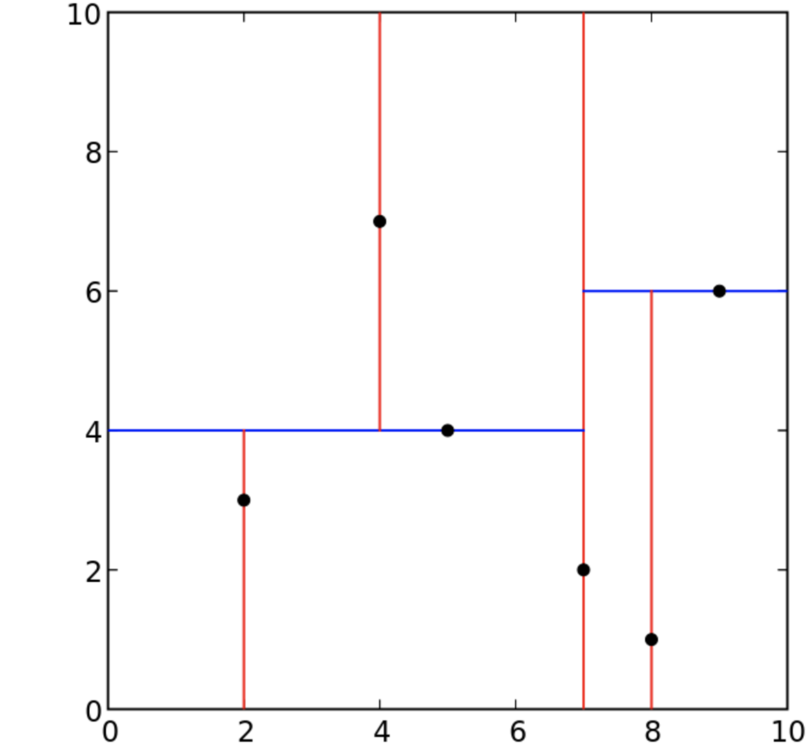
k-d tree

- k-dimensional binary search tree
- Robotics: typically 3D or 2D
- Every level of tree:
  - For a different axis (e.g. x,y,z,x,y,z,x,y,z) (=> split space with planes)
  - Put points in left or right side based on median point (w.r.t. its value of on the current axis) =>
  - Balanced tree
- Fast neighbor search -> ICP!

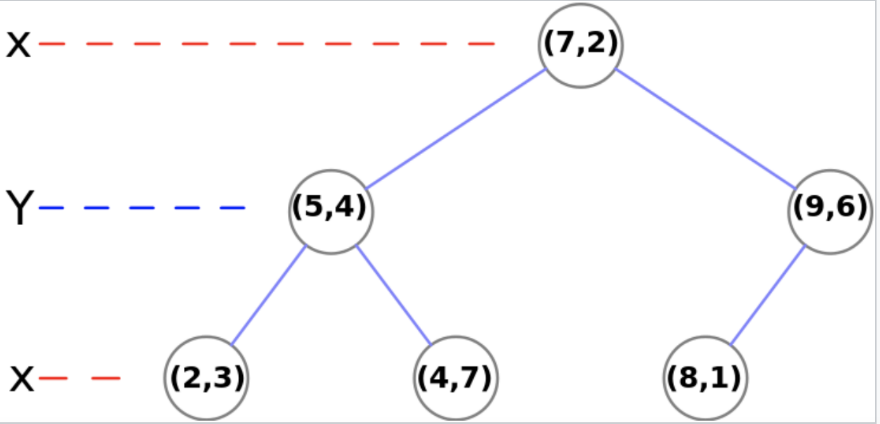


Algorithm	Average	Worst case
Space	$O(n)$	$O(n)$
Search	$O(\log n)$	$O(n)$
Insert	$O(\log n)$	$O(n)$
Delete	$O(\log n)$	$O(n)$





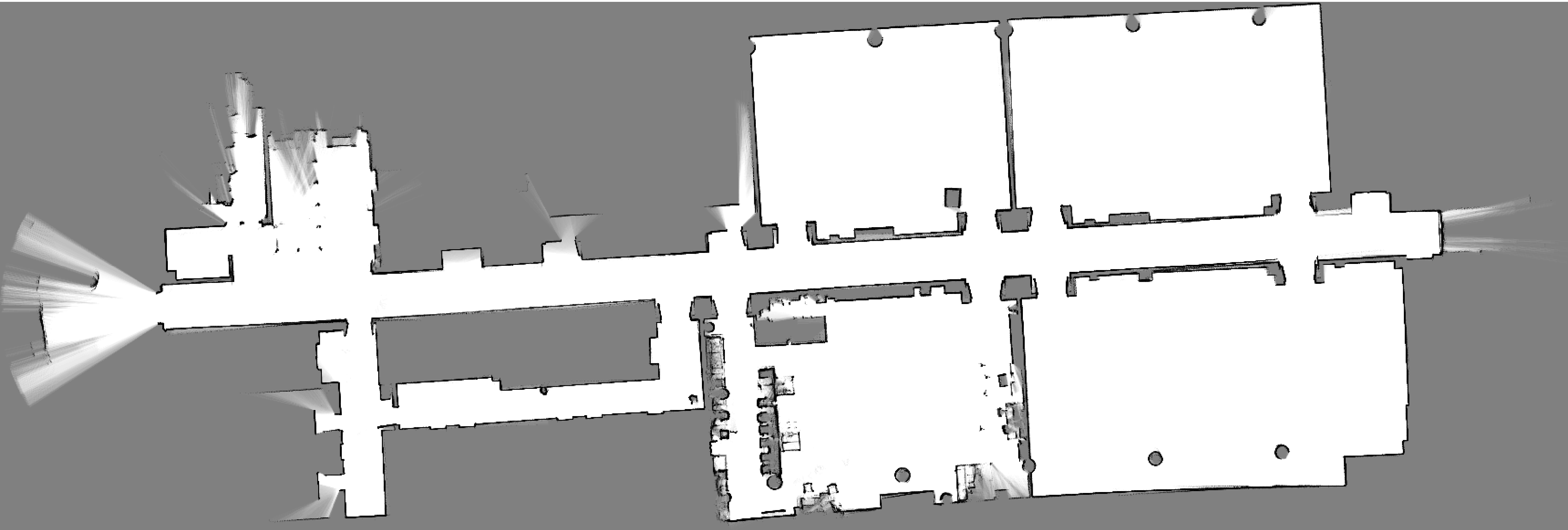
k-d tree decomposition for the point set `(2,3), (5,4), (9,6), (4,7), (8,1), (7,2)`.



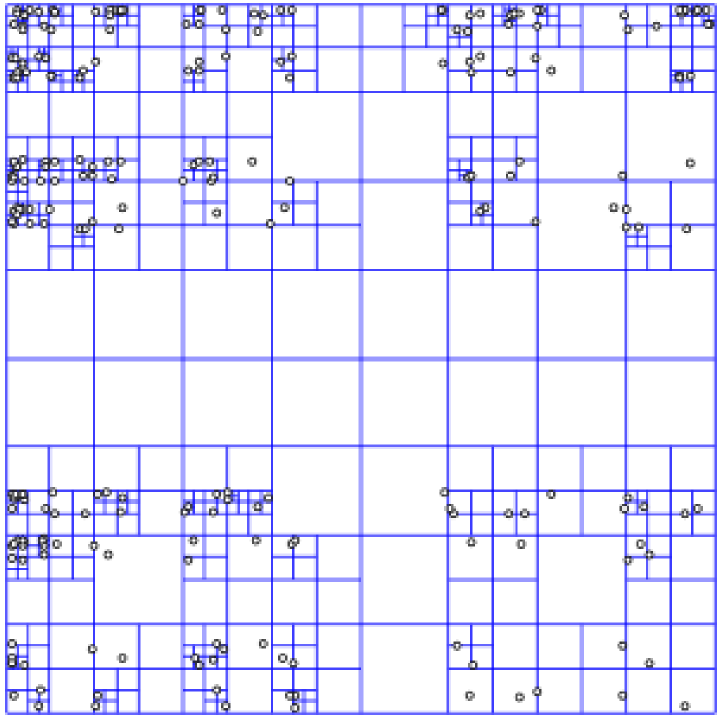
The resulting *k*-d tree.

Probabilistic grid map

- 1: occupied; 0: free; 0.5: unknown
- Need error model of sensor (and of localization) to properly update cells with a scan
- Can remove dynamic (moving) objects (by observing the free space multiple times)



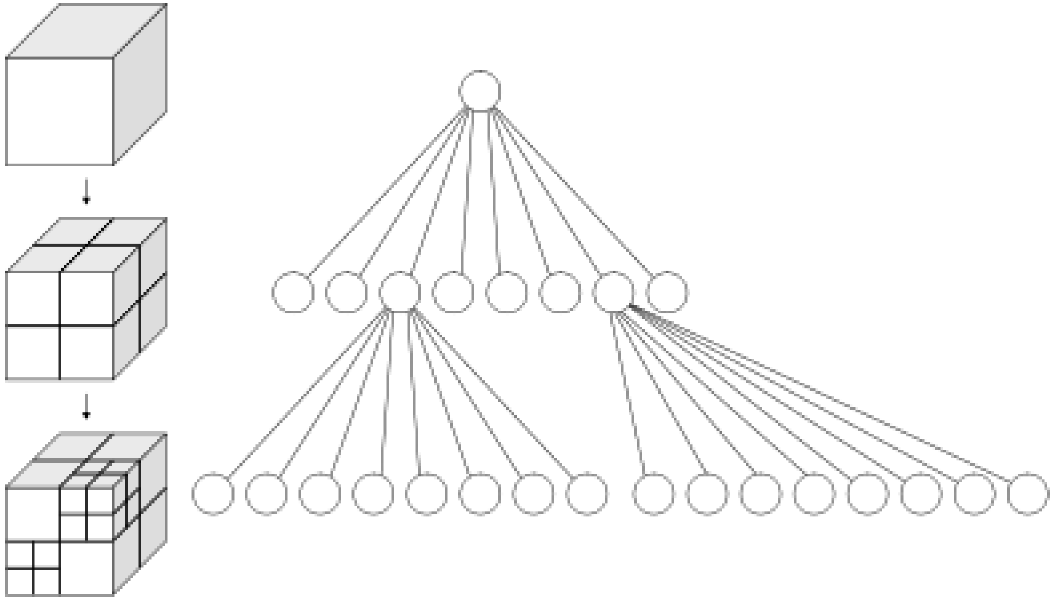
Adaptive Cell Decomposition

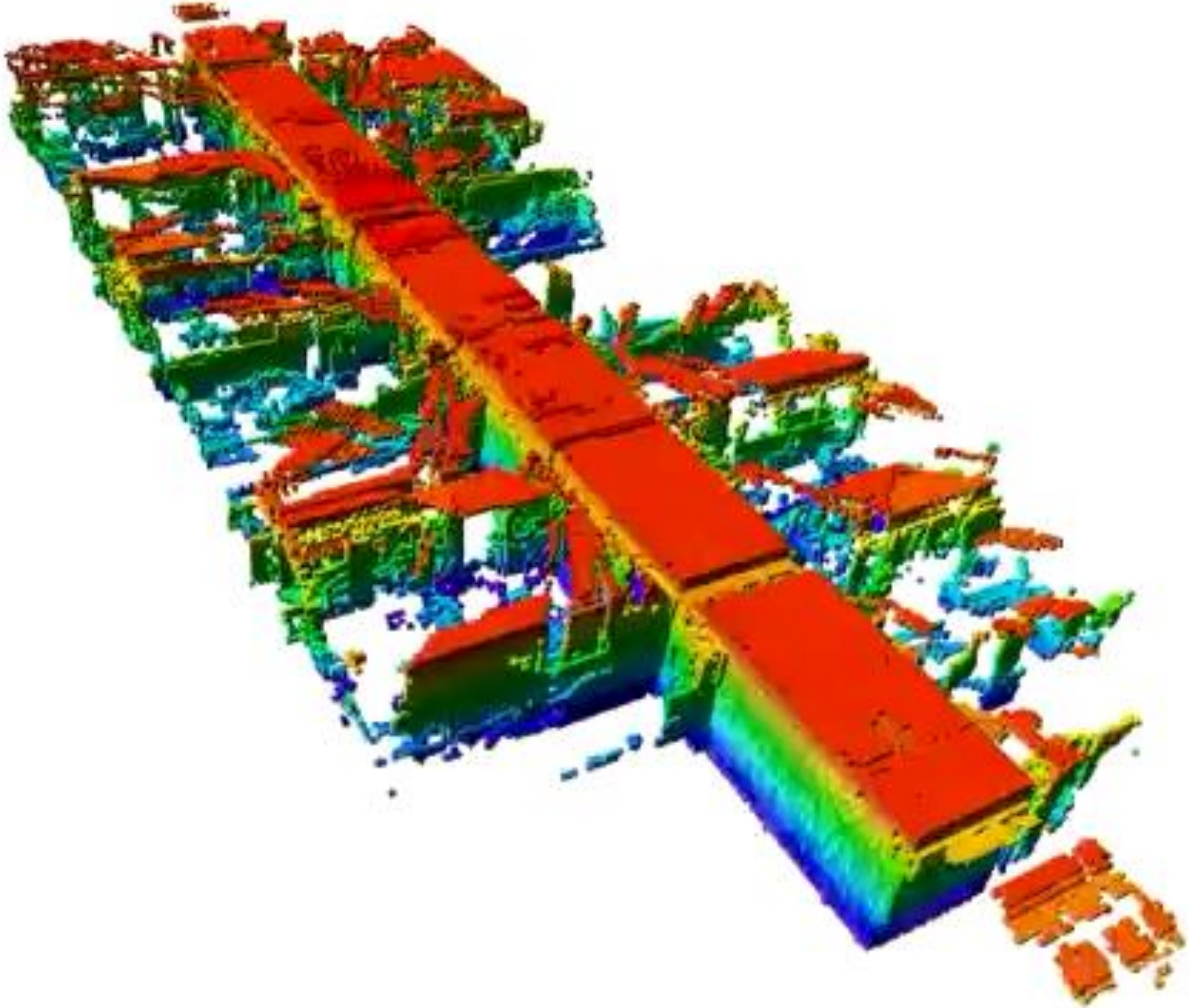


- Quad-tree
  - 2D map/ grid is recursively divided into 4 smaller cells
  - Only cells with different values/ points get divided further =>
  - Compact representation of big space (if many cells stay merged)

- Oct-tree
  - 3D grid divided into 8 smaller cells
  - Very compact! (There is lots of free space!)

- OctoMap: probabilistic oct-tree!
  - http://octomap.github.io
  - Good support in ROS (e.g. MoveIt!)





Semantic Information

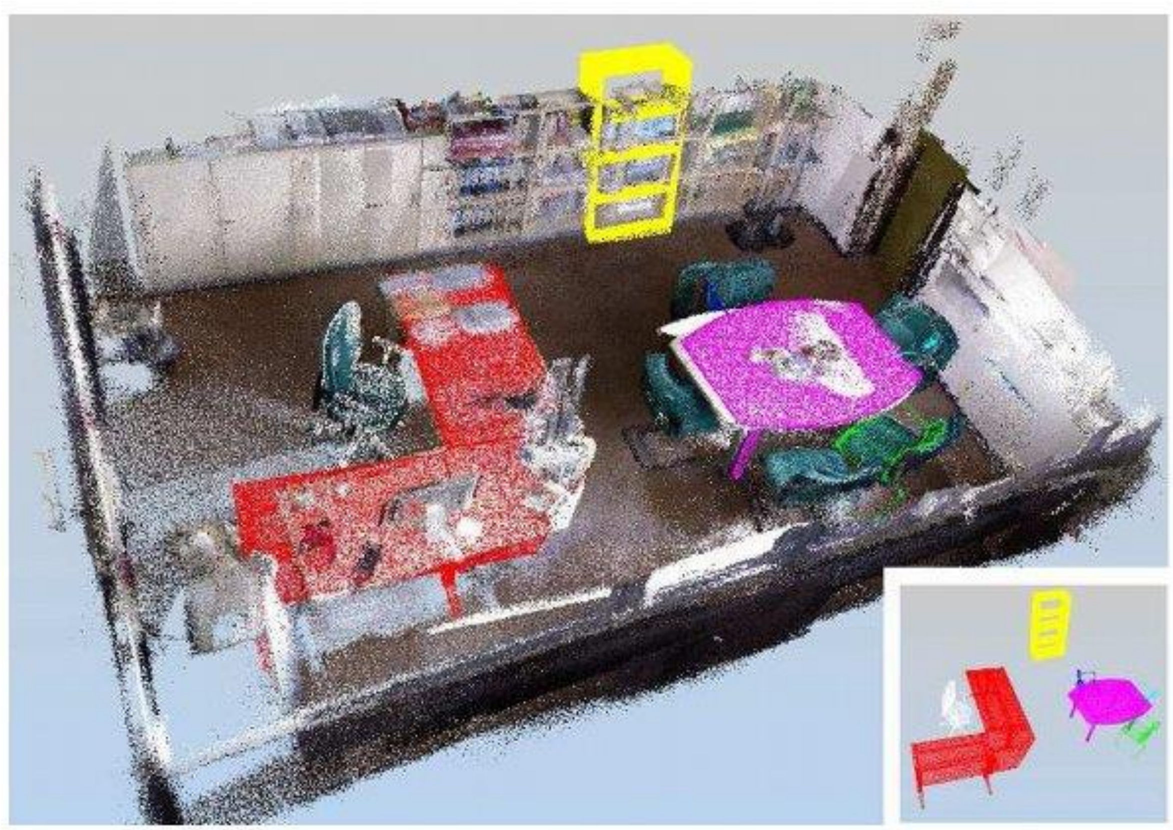
- Assign labels to data
- Segmentation: automatically group data (e.g. points) according to their semantic class

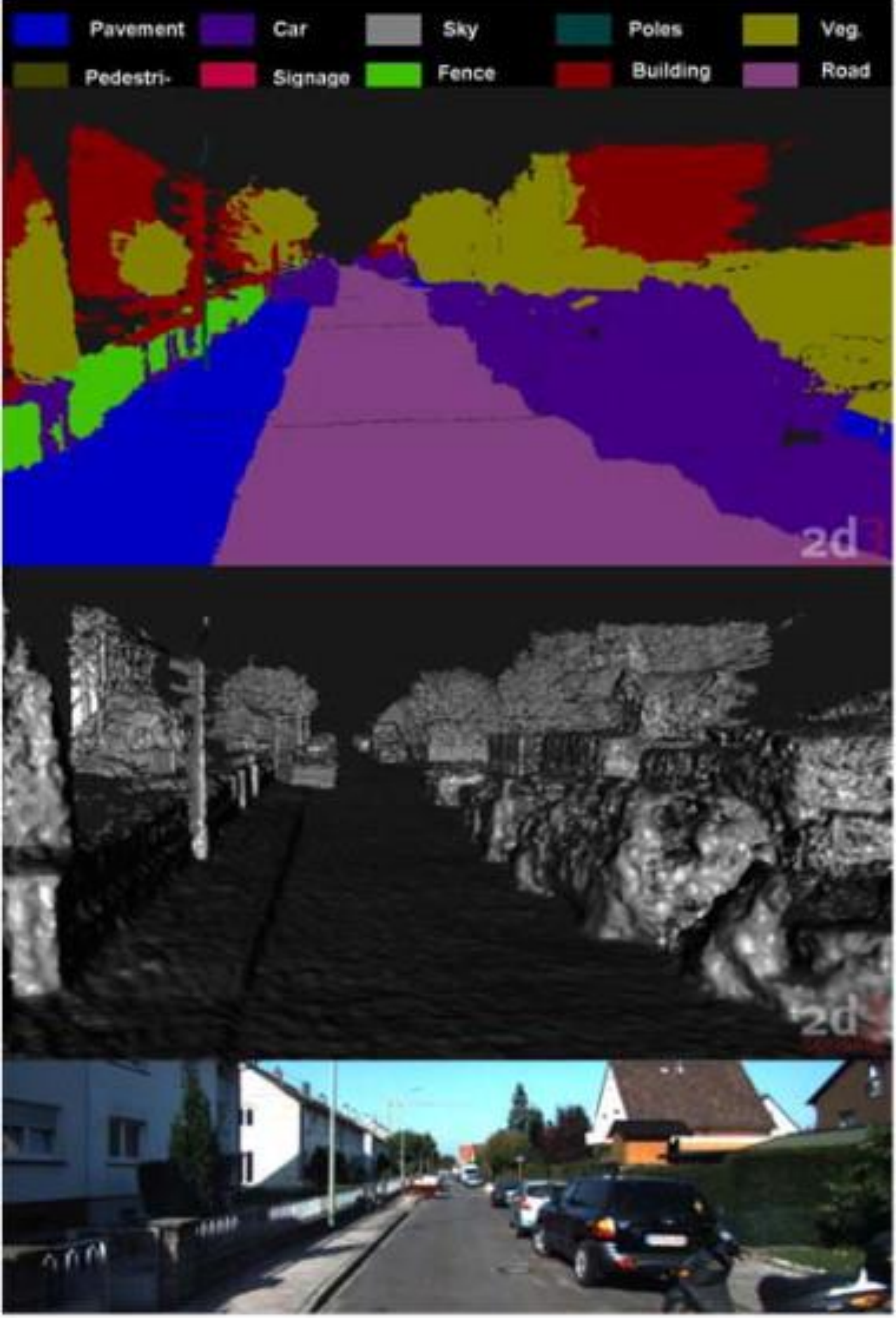
- Even save just very high level data; e.g. room at (x,y); Eiffel tower; …

- Applications:
  - Human Robot Interaction (“go to kitchen”)
  - Scene understanding
  - Navigation (detect road; detect door)
  - Localization
  - …

Semantic Map

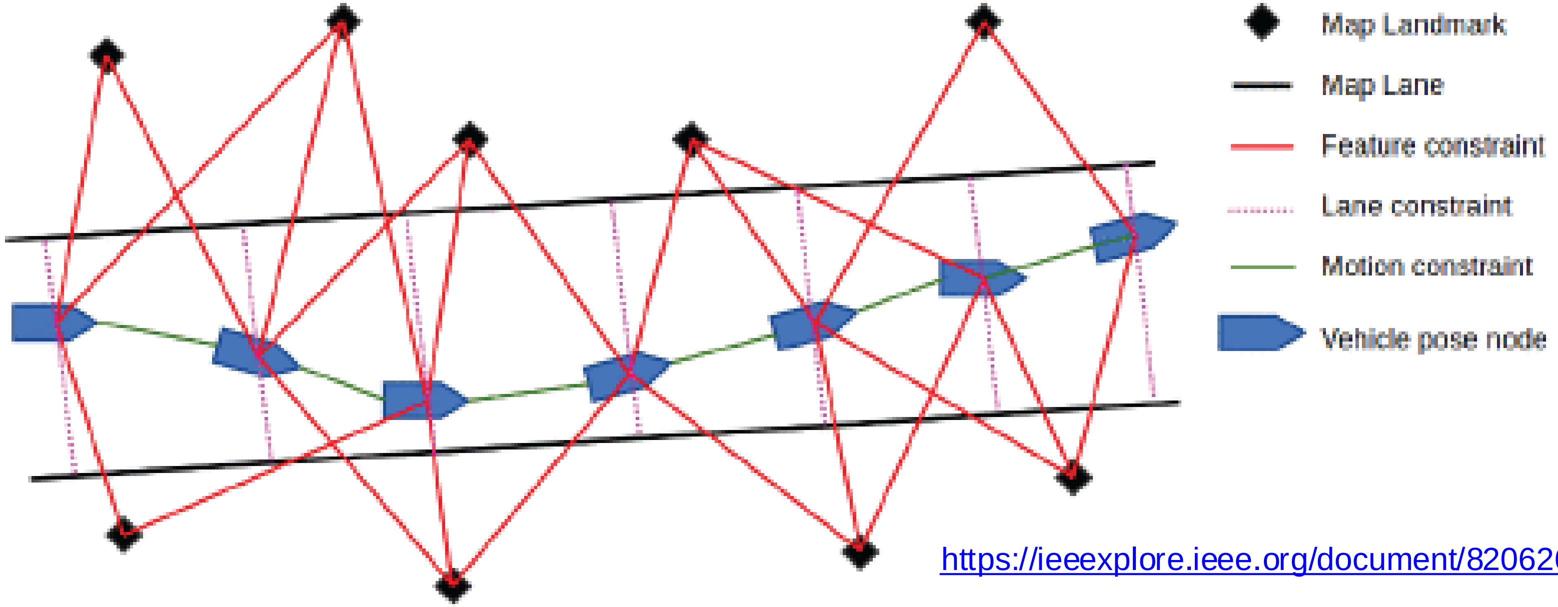
- Semantic Segmentation
  - In room (e.g. detect furniture & objects)
  - Outdoors





Pose Graph

- Graph structure
- Nodes are:
  - Robot
  - Landmarks/ observations



https://ieeexplore.ieee.org/document/8206264

- Used for Simultaneous Localization and Mapping (some more details later today)

- Typically saves (raw) sensor data in robot nodes =>
- For most applications: needs to be rendered before using it:
  put all sensor data in common frame in a point cloud or grid map or plane map or ...

Mapping

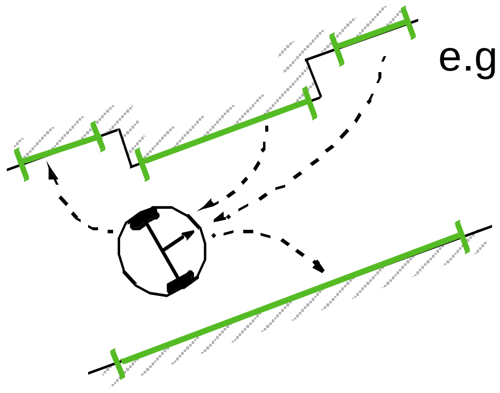
- Process of building a map
- Basic principle:
  1. Initialize the map with unknown or free
  2. Take a sensor scan
  3. Maybe pre-process it (e.g. plane detection)
  4. Localize the robot w.r.t. the map frame (maybe difficult!)
  5. Transform the (processed) sensor scan to the global frame
  6. “Merge” the new data with the old map data, e.g.:
     - Add scanned points to map point cloud
     - Update cells in a probabilistic occupancy grid
  7. Sometimes: Also do ray-casting to mark all cells from sensor to obstacle as free
  8. Repeat for every new sensor scan

- Localization step may need the map (e.g. matching the scan against the map) => both should be done at the same time =>
- Simultaneous Localization and Mapping : SLAM

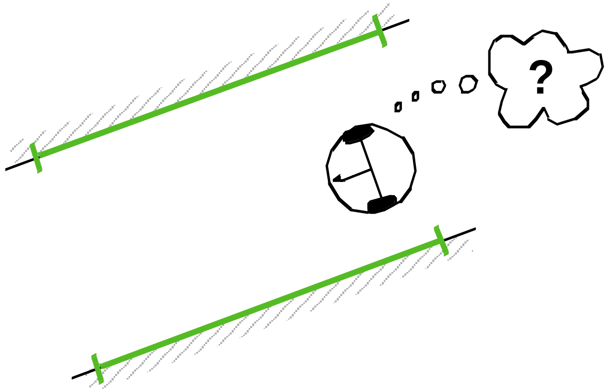
SIMULTANEOUS LOCALIZATION AND MAPPING - SLAM

Map Building: The Problems

1. **Map Maintaining:** Keeping track of changes in the environment



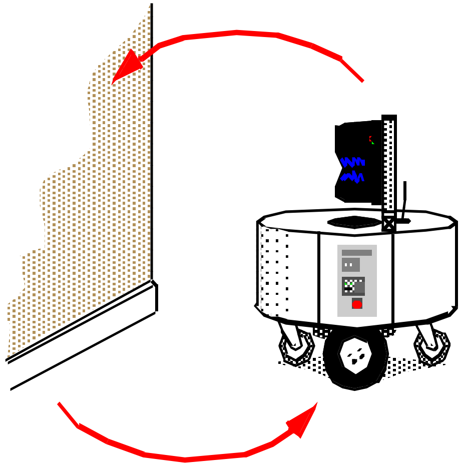
e.g. disappearing cupboard



- e.g. measure of belief of each environment feature

2. **Representation and Reduction of Uncertainty**

position of robot -> position of wall

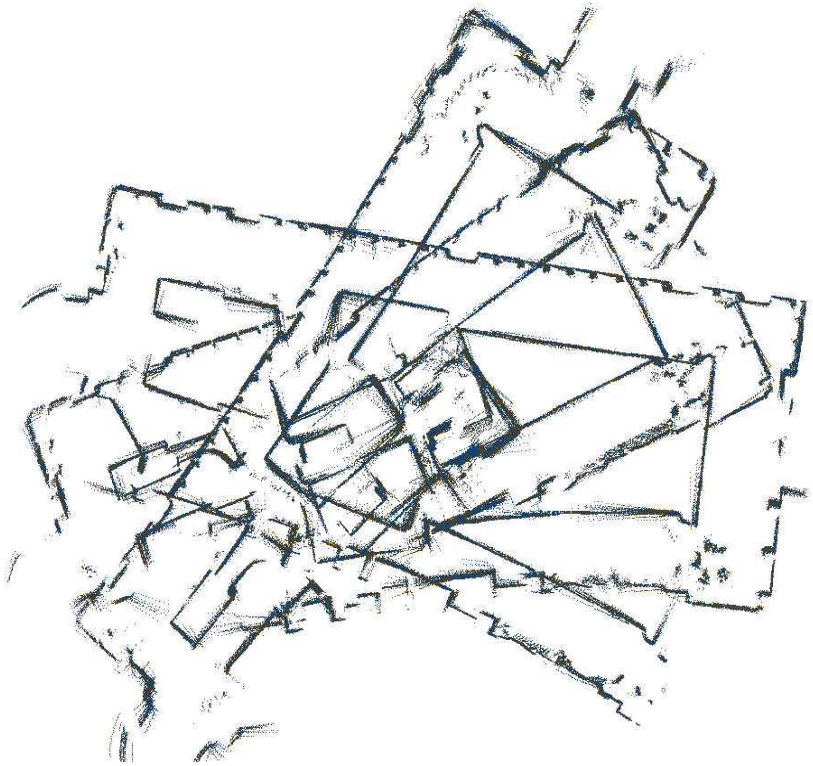


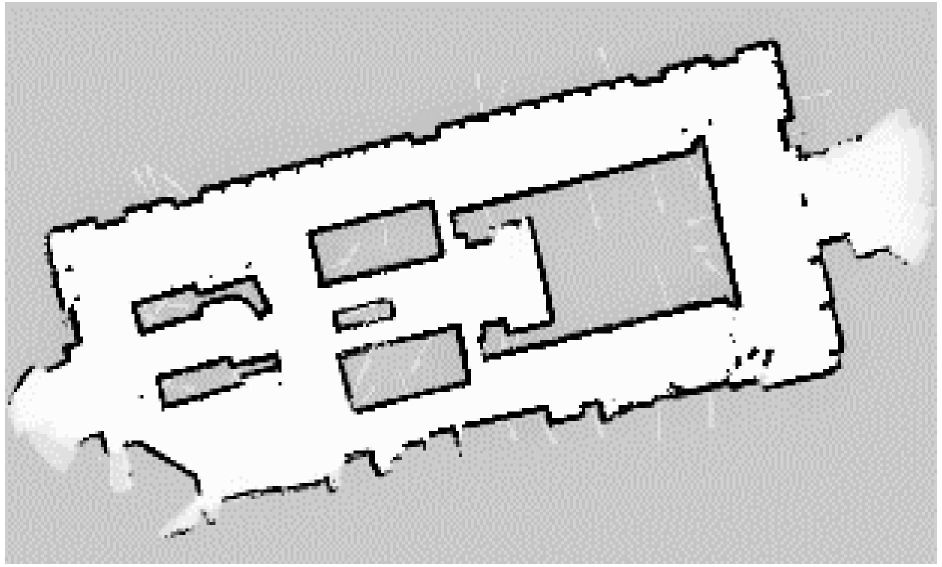
position of wall -> position of robot

- probability densities for feature positions
- Inconsistent map due to motion drift

Cyclic Environments

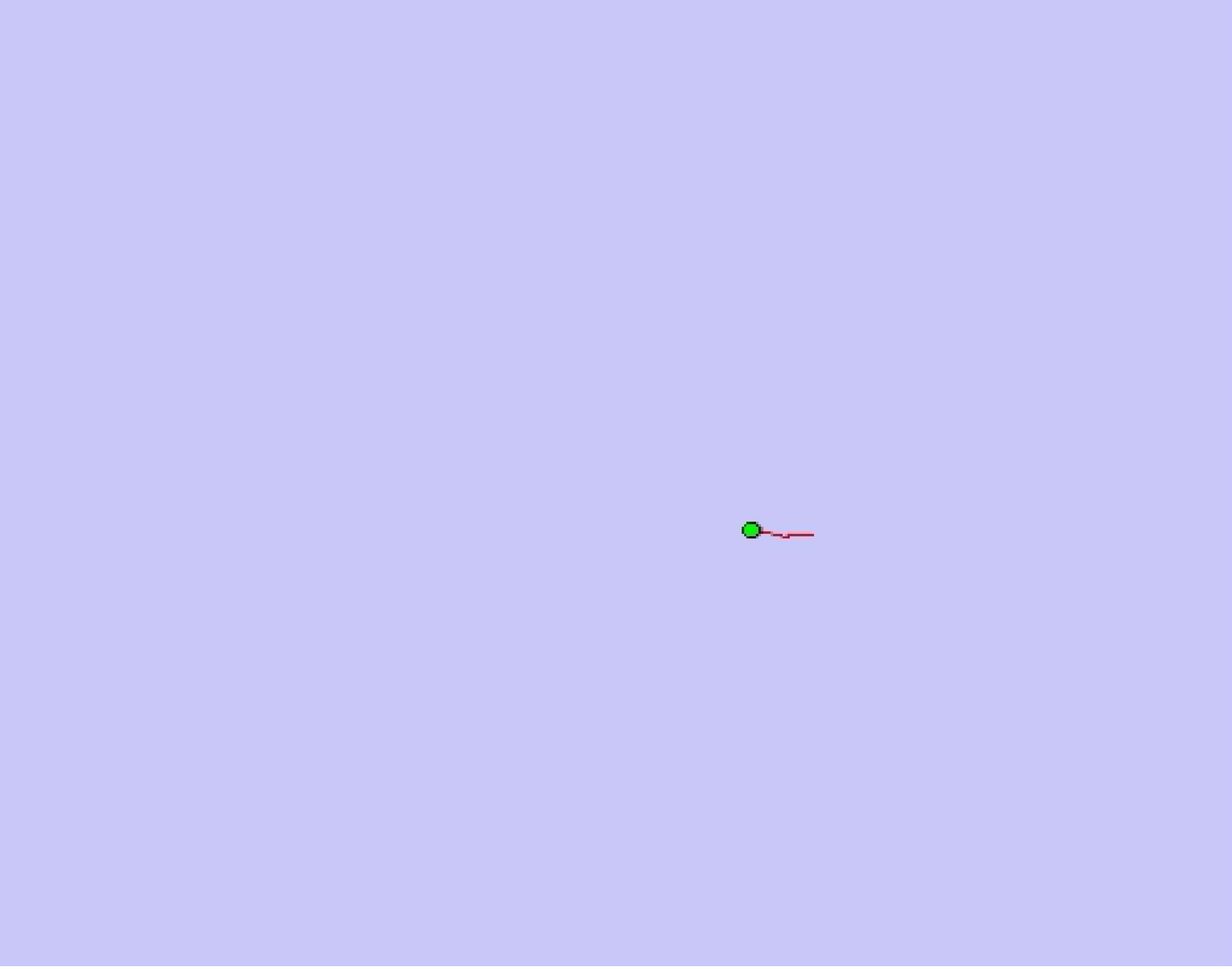
- Small local error accumulate to arbitrary large global errors!
- This is usually irrelevant for navigation
- However, when closing loops, global error does matter





Raw Odometry

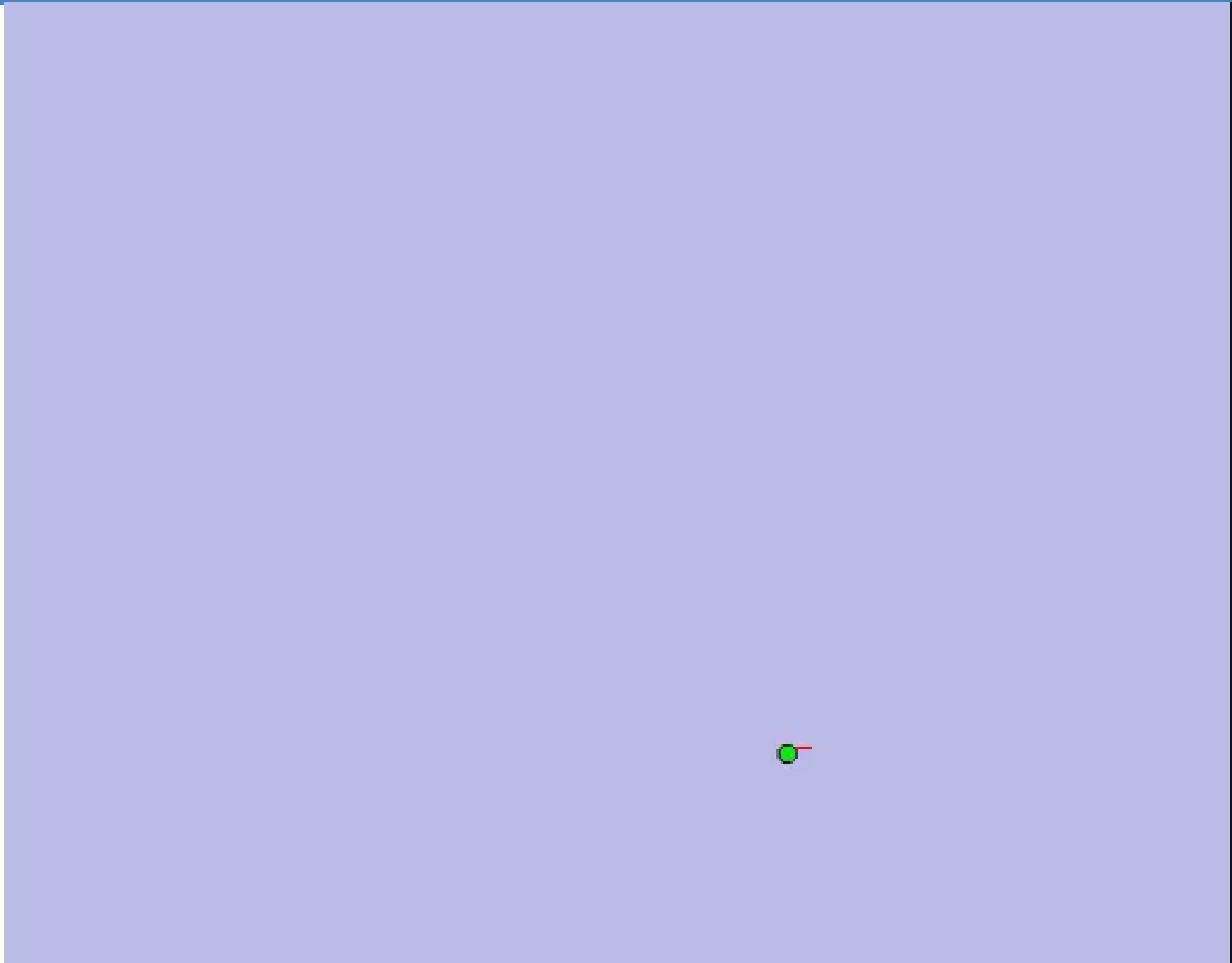
- Famous Intel Research Lab dataset (Seattle) by Dirk Hähnel



Courtesy of S. Thrun

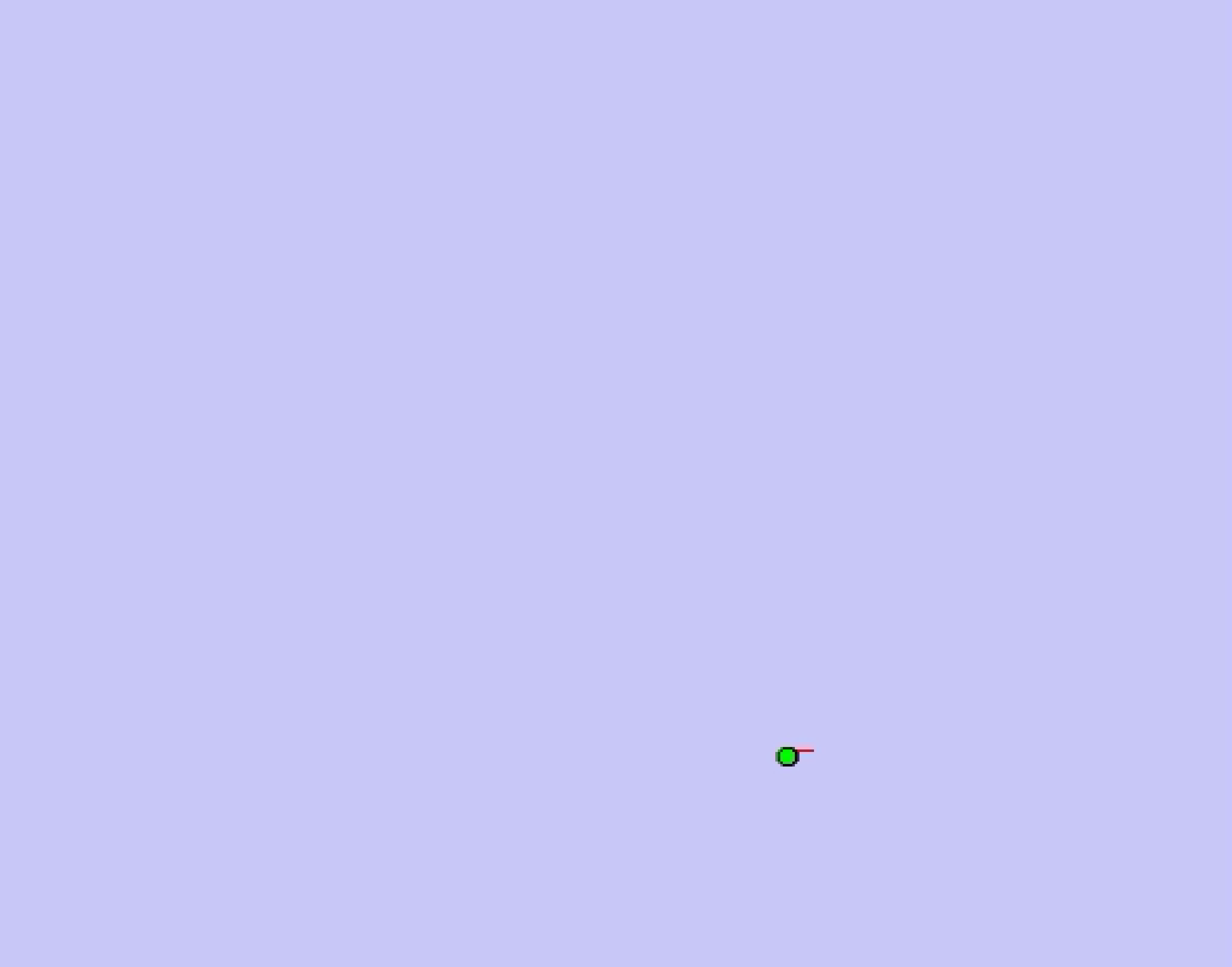
http://robots.stanford.edu/videos.html

Scan Matching: compare to sensor data from previous scan



Courtesy of S. Thrun

FastSLAM: Particle-Filter SLAM



Courtesy of S. Thrun

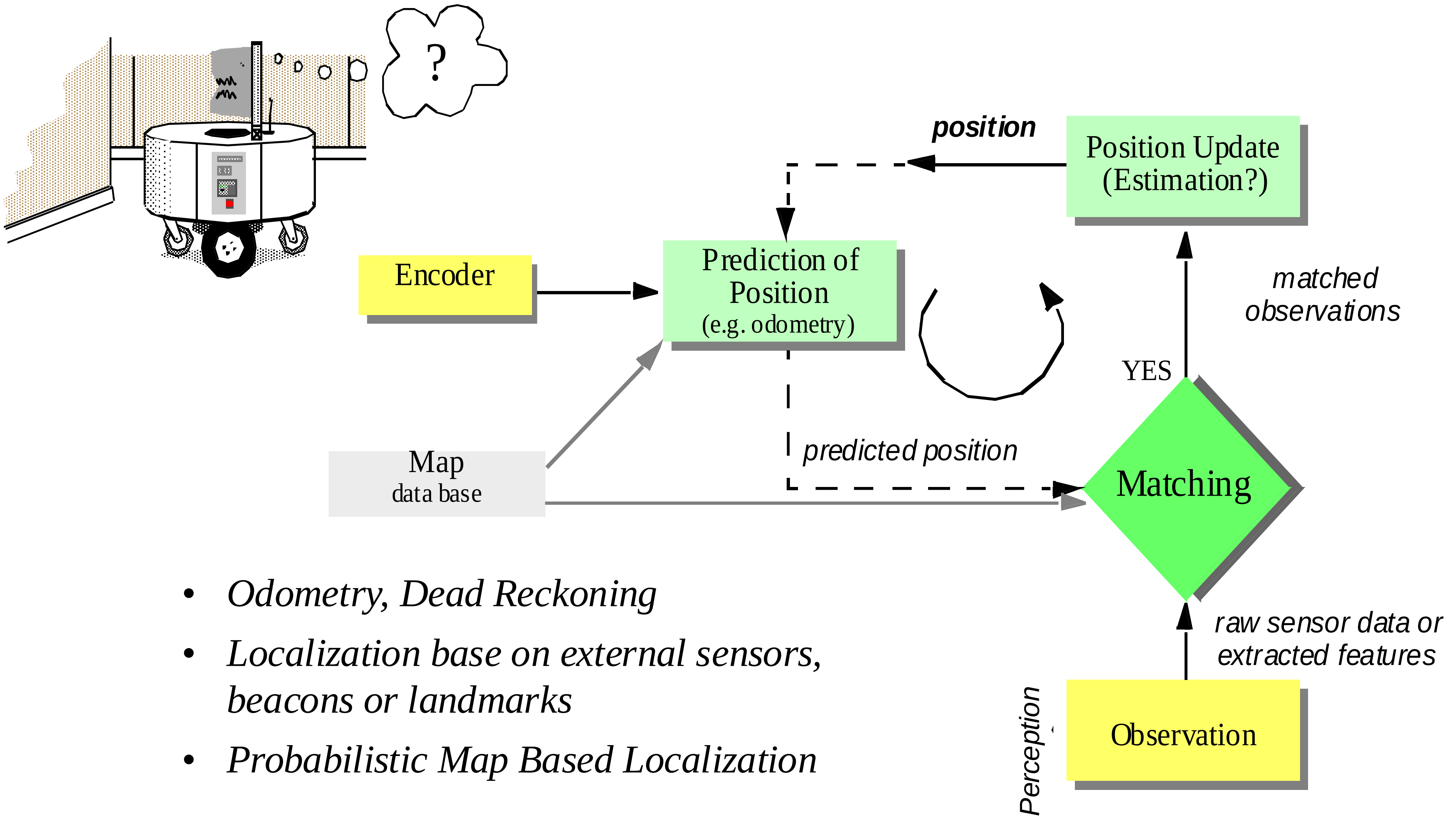
Scan Matching/ Registration

- Take one sensor scan
- Match against:
  - Another sensor scan
  - Against the map

- Output:
  - The Transform (2D: 3DoF; 2D: 6DoF; each maybe with scale)
  - Uncertainty about the result (e.g. covariance matrix)

- Used for Localization:
  - Typical algorithms for point clouds: ICP!

Map based localization



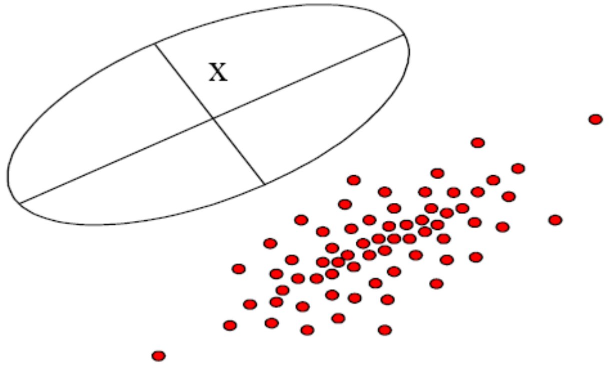
- *Odometry, Dead Reckoning*
- *Localization base on external sensors, beacons or landmarks*
- *Probabilistic Map Based Localization*

Localization

- Based on control commands => Open Loop!
- Wheel odometry
  - Compass, Accelerometer, Gyro => IMU
- Scan Matching of Range Sensors == Registration (rigid => no scaling or shearing)
  - ICP: scan to scan or scan to map
    - Needs good initial guess
  - NDT registration
  - Feature-based registration
  - Direct/ optimization based registration
- Grid-based Localization
- Kalman Filter Based Localization
- Monte-Carlo Localization (MCL) == Particle Filter
  - Adaptative MCL => AMCL
- Visual Odometry (VO)
  - With IMU: Visual Inertial Odometry (VIO)
- SLAM techniques
- 3D Reconstruction
  - Structure from Motion/ Bundle Adjustment
  - Localization is by-product
- Absolute Localization:
  - GPS
  - Markers (e.g. QR code)
  - Landmarks (e.g. ShanghaiTech Tower)

Monte Carlo Localization (MCL)

- Input: Global, known map and laser scan
- Particle filter: set of particles representing a robot state
  - Here: robot pose (position & orientation)
  - Particle filter SLAM (e.g. FastSLAM): also map!
  - Particles are sampled based on probability distribution
- Assign weights (scores) to particles based on how well the scan matches to the map, given this pose
- Markov property: Current state only depends on previous state



probability distribution (ellipse) as particle set (red dots)

- Algorithm:

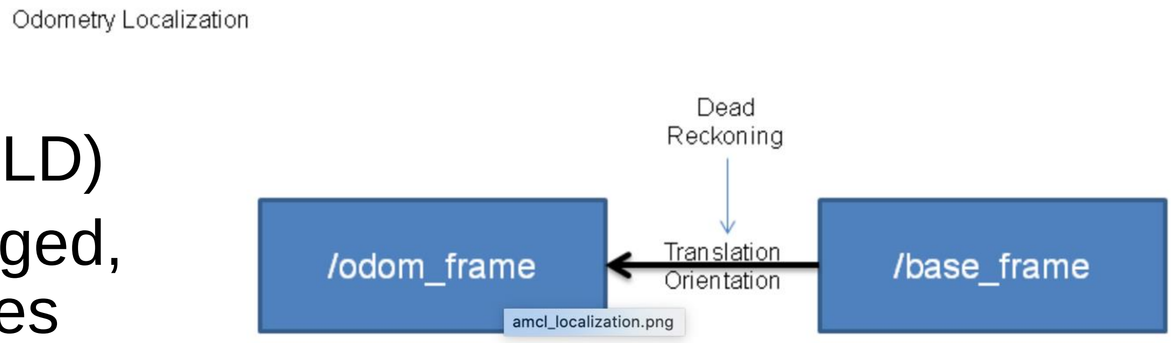
1. For all particles:
   1. Apply motion update (e.g. odometry)
   2. Apply the sensor update (scan match) and calculate new weights
2. Re-Sample particles based on their weights

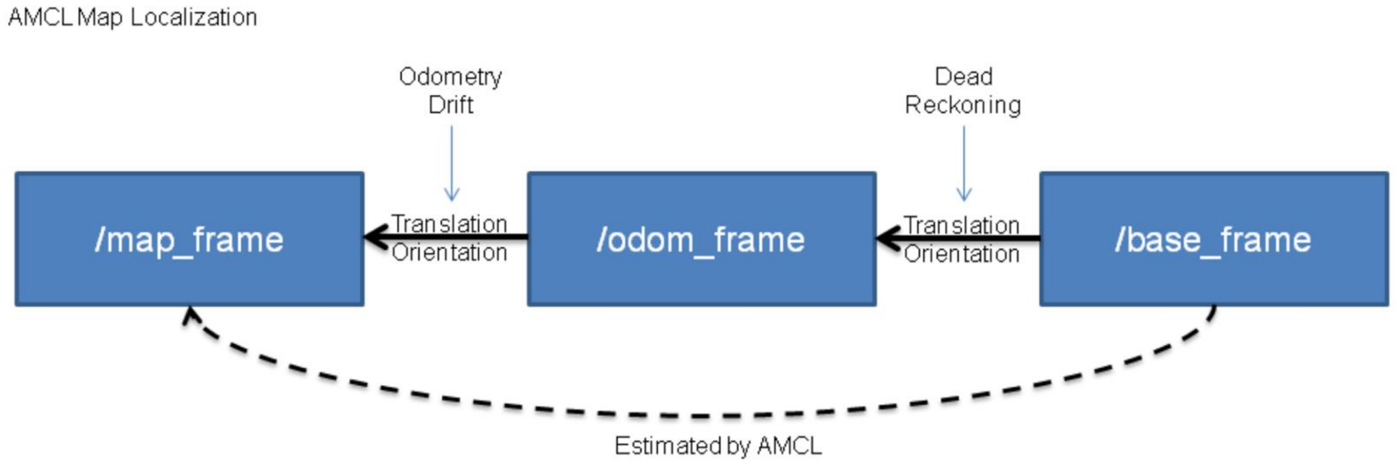
- Can solve the kidnapped robot problem (also wake-up robot problem)
- Problem: Particle of correct pose might not exist…

Adaptive Monte Carlo Localization (AMCL)

- Sample particles adaptively
  - Based on error estimate
  - Kullback-Leibler divergence (KLD)
  - => when particles have converged, have a fewer number of particles

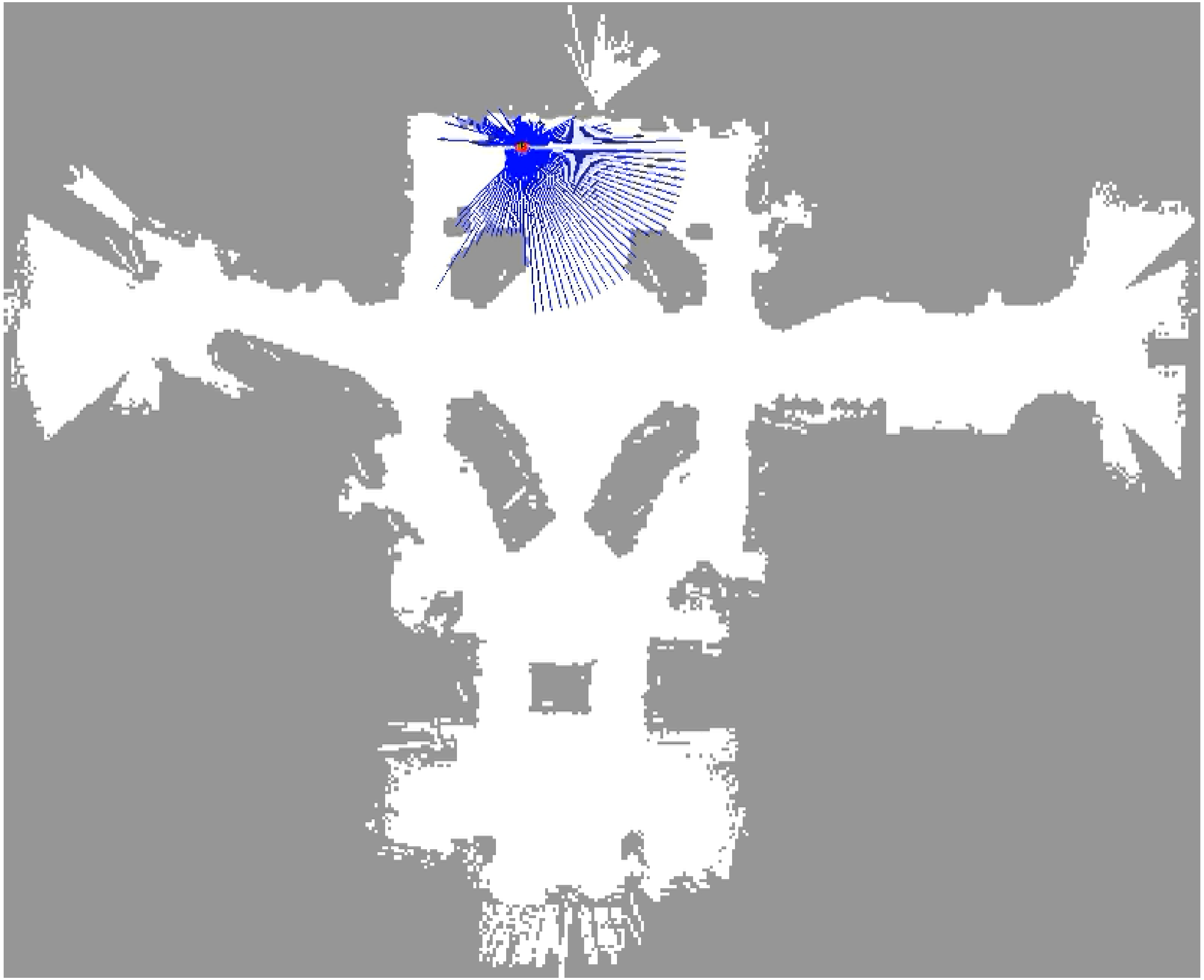
  - Sample size is re-calculated each iteration



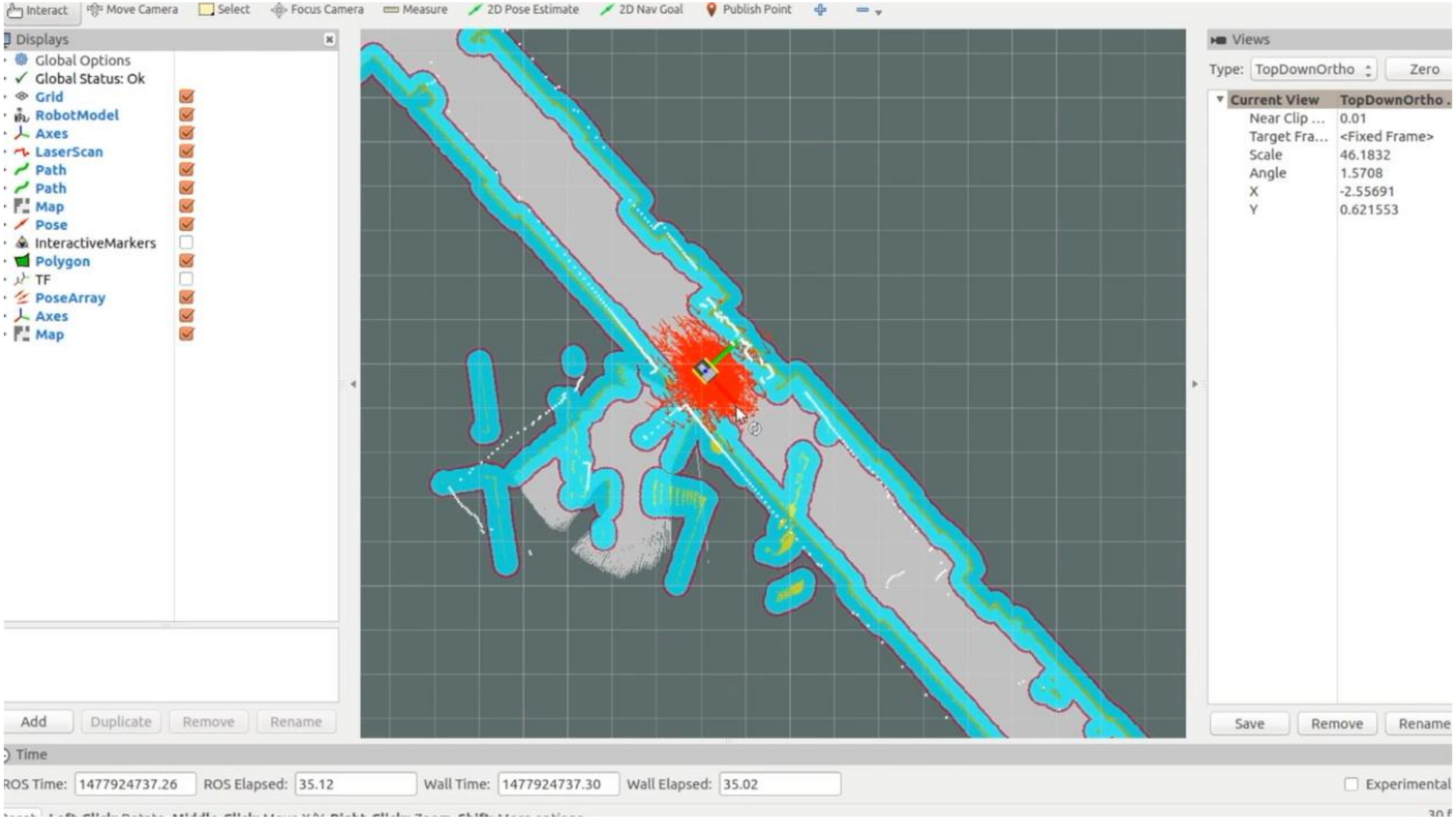


- http://wiki.ros.org/amcl
- Used by the ROS Navigation stack

MCL & Robot Kidnapping



AMCL in ROS



☑ Grid
☑ RobotModel
☑ Axes
☑ LaserScan
☑ Path
☑ Path
☑ Map
☑ Pose
□ InteractiveMarkers
☑ Polygon
□ TF
☑ PoseArray
☑ Axes
☑ Map

Type: TopDownOrtho

Current View	TopDownOrtho ...
Near Clip ...	0.01
Target Fra...	<Fixed Frame>
Scale	46.1832
Angle	1.5708
X	-2.55691
Y	0.621553

ROS Time: 1477924737.26 ROS Elapsed: 35.12 Wall Time: 1477924737.30 Wall Elapsed: 35.02 □ Experimental

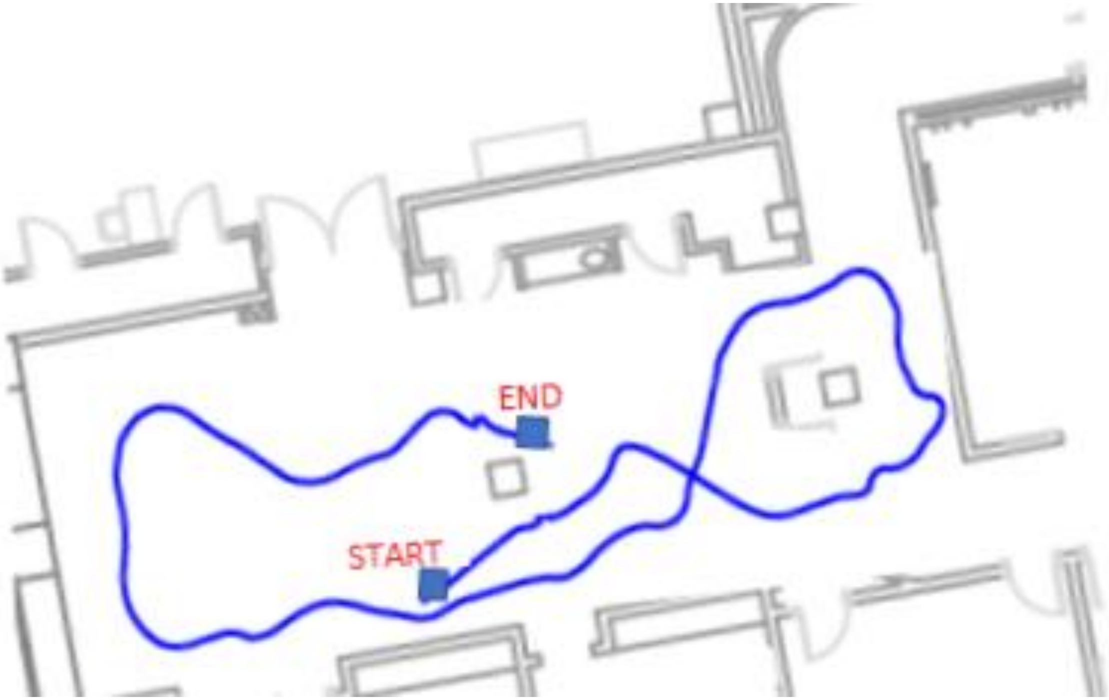
Overview of SLAM Methods

- Camera
  - Feature-Based Methods
    - MonoSLAM
    - PTAM
    - ORB-SLAM
  - Direct Methods
    - DTAM
    - LSD-SLAM
    - DSO
  - Semi-Direct Methods
    - SVO
  - Others
    - PoseNet
    - CNN-SLAM
    - …

- Laser
  - Pose Graph
    - Cartographer
    - Karto-SLAM
    - Hector-SLAM
    - BLAM
    - LIO
  - Particle Filter
    - FastSLAM
    - Gmapping
  - Extended Kalman Filter
    - EKF-SLAM
    - LINS
  - Others
    - LOAM
    - IMLS-SLAM
    - …

SLAM Front-end & Back-end

- Front-end
  - calculate relative poses between several frames/ to map
    - scan matching
    - image registration
    - …
  - estimate absolute poses
  - construct the local map
- Back-end
  - optimize the absolute poses and mapping
  - only if a loop was closed



https://ww2.mathworks.cn/help/nav/ug/implement-simultaneous-localization-and-mapping-with-lidar-scans.html

THREE SLAM PARADIGMS

The Three SLAM Paradigms

- Most of the SLAM algorithms are based on the following three different approaches:
  - Extended Kalman Filter SLAM: (called EKF SLAM)
  - Particle Filter SLAM: (called FAST SLAM)
  - Graph-Based SLAM

EKF SLAM: overview

- **Extended state vector** $\boldsymbol{y_t}$: robot pose $\boldsymbol{x_t}$ + position of all the features $\boldsymbol{m_i}$ in the map:

$$y_t = [x_t, m_0, \dots, m_{n-1}]^T$$

- Example: 2D line-landmarks, size of $\boldsymbol{y_t}$ = $3+2n$: three variables to represent the robot pose + $2n$ variables for the n line-landmarks having vector components

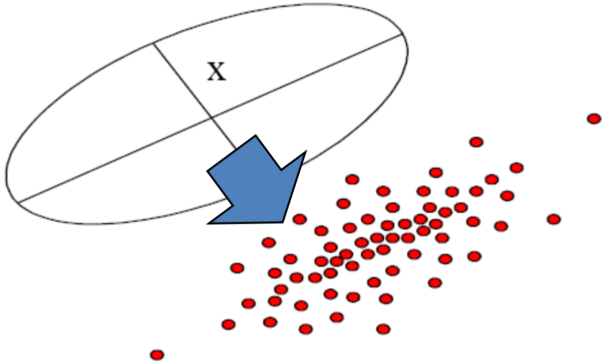
$$(\alpha_i, r_i)$$

$$y_t = [x_t, y_t, \theta_t, \alpha_0, r_0, \dots, \alpha_{n-1}, r_{n-1}]^T$$

- As the robot moves and takes measurements, the state vector and covariance matrix are updated using the standard equations of the extended Kalman filter
- Drawback: EKF SLAM is computationally very expensive.

Particle Filter SLAM: FastSLAM

- **FastSLAM approach**
  - Using particle filters.
  - Particle filters: mathematical models that represent probability distribution as a set of discrete particles that occupy the state space.



probability distribution (ellipse) as particle set (red dots)

- Particle filter update
  - Generate new particle distribution using motion model and controls

a) For each particle:

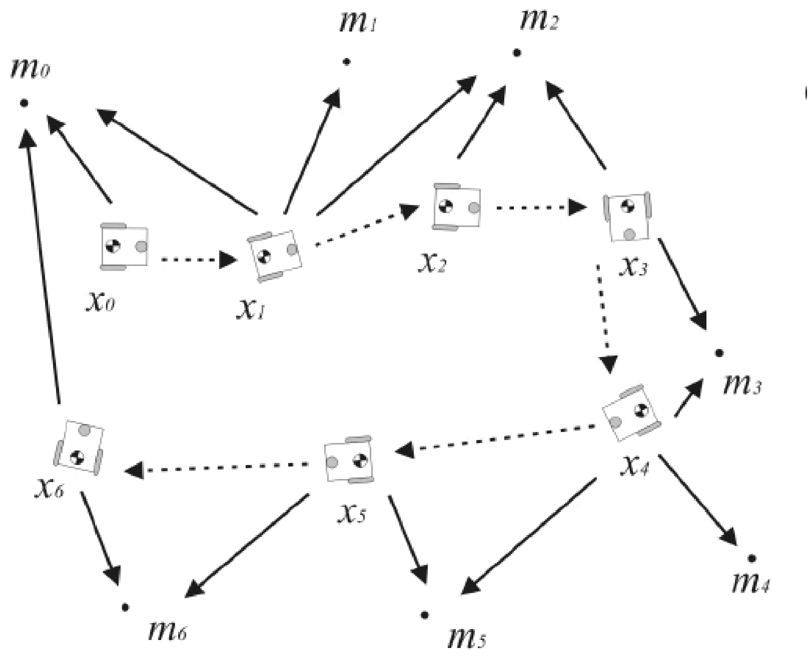
1. Compare particle’s prediction of measurements with actual measurements
2. Particles whose predictions match the measurements are given a high weight

b) Filter resample:

- Resample particles based on weight
- Filter resample
  - Assign each particle a weight depending on how well its estimate of the state agrees with the measurements and randomly draw particles from previous distribution based on weights creating a new distribution.

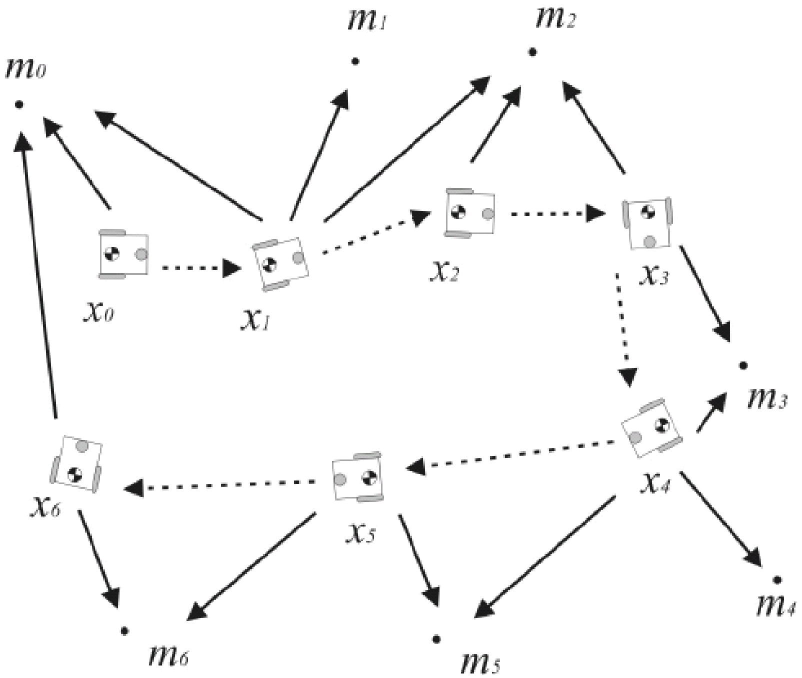
Graph-Based SLAM (1/3)

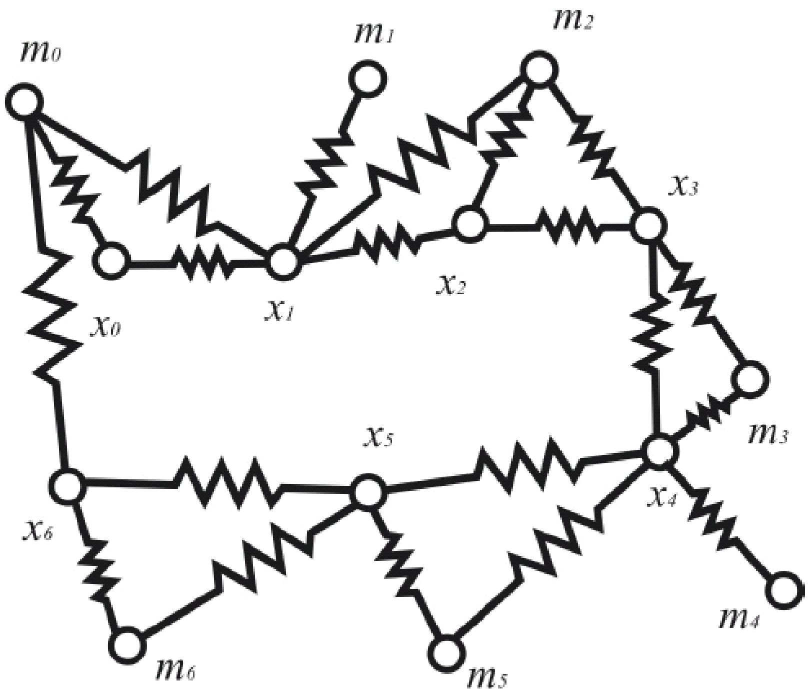
- SLAM problem can be interpreted as a sparse graph of nodes and constraints between nodes.
- The nodes of the graph are the robot locations and the features in the map.
- Constraints: relative position between consecutive robot poses , (given by the odometry input ***u***) and the relative position between the robot locations and the features observed from those locations.



Graph-Based SLAM (2/3)

- Constraints are not rigid but soft constraints!
- Relaxation: compute the solution to the full SLAM problem =>
  - Compute best estimate of the robot path and the environment map.
  - Graph-based SLAM represents robot locations and features as the nodes of an elastic net. The SLAM solution can then be found by computing the state of minimal energy of this net



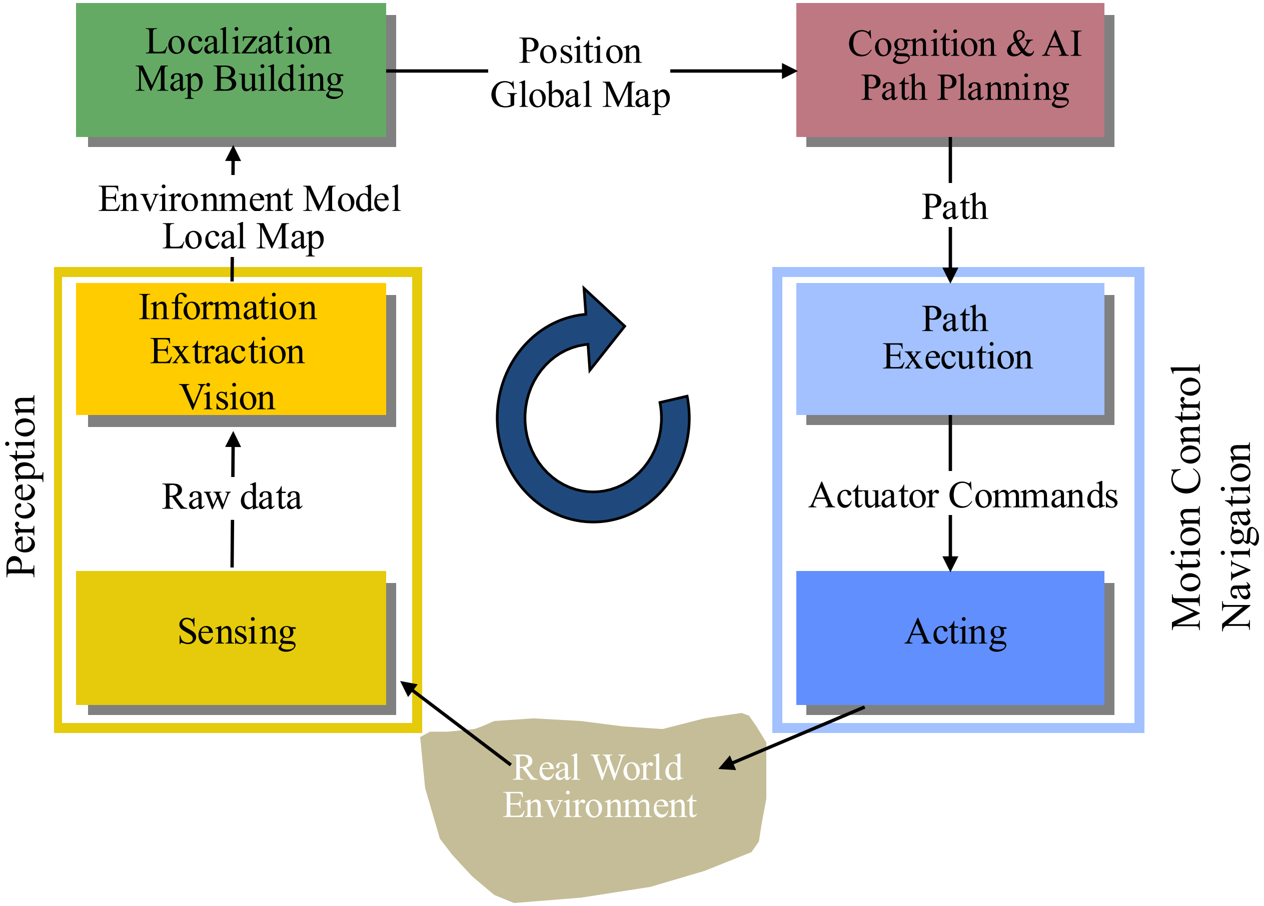


Graph-Based SLAM (3/3)

- Significant advantage of graph-based SLAM techniques over EKF SLAM:
  - EKF SLAM: computation and memory for to update and store the covariance matrix is quadratic with the number of features.
  - Graph-based SLAM: update time of the graph is constant and the required memory is linear in the number of features.
- However, the final graph optimization can become computationally costly if the robot path is long.
- Libraries for graph-based slam: g2o, ceres

PLANNING

General Control Scheme for Mobile Robot Systems

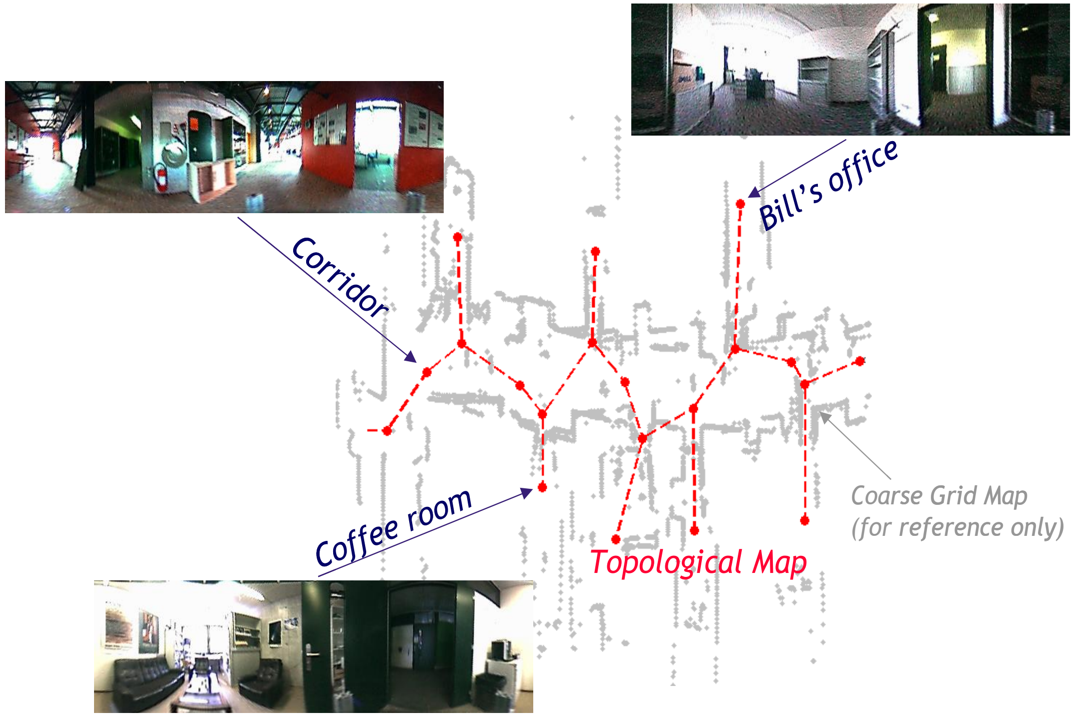


With material from Roland Siegwart and Davide Scaramuzza, ETH Zurich

The Planning Problem

- The problem: find a path in the work space (physical space) from the initial position to the goal position avoiding all collisions with the obstacles

- Assumption: there exists a good enough map of the environment for navigation.

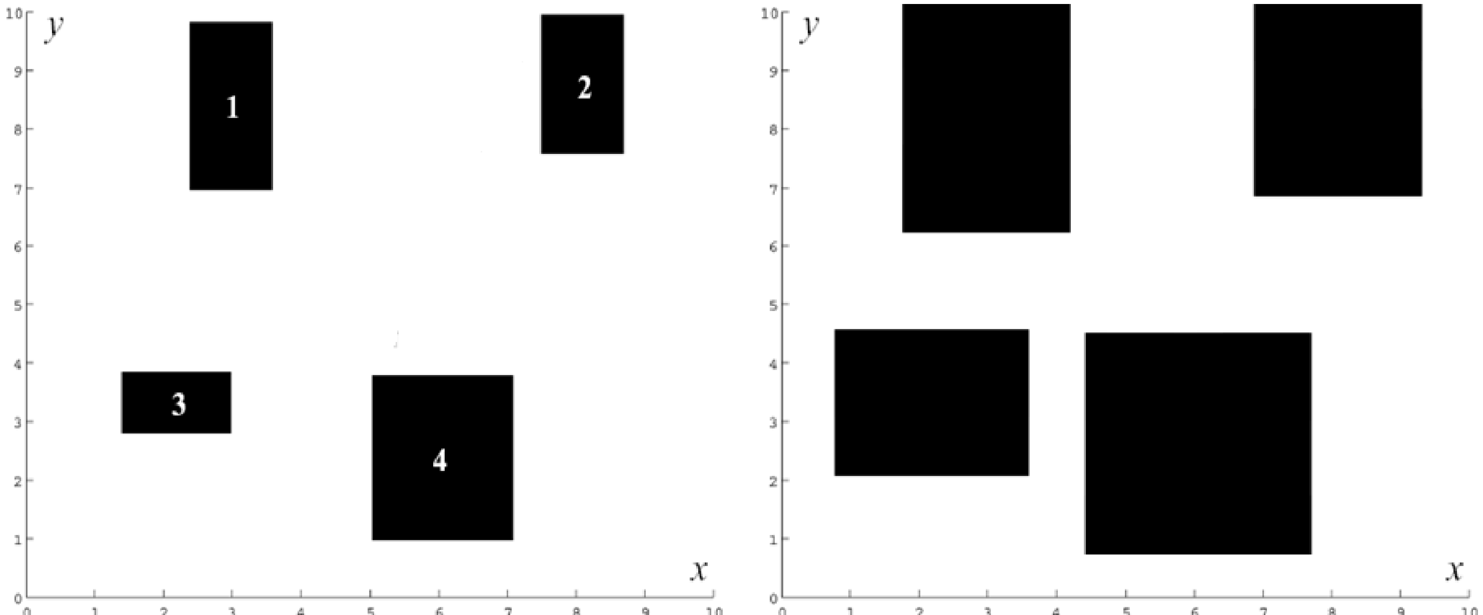


The Planning Problem

- We can generally distinguish between
  - (global) path planning and
  - (local) obstacle avoidance.
- First step:
  - Transformation of the map into a representation useful for planning
  - This step is planner-dependent
- Second step:
  - Plan a path on the transformed map
- Third step:
  - Send motion commands to controller
  - This step is planner-dependent (e.g. Model based feed forward, path following)

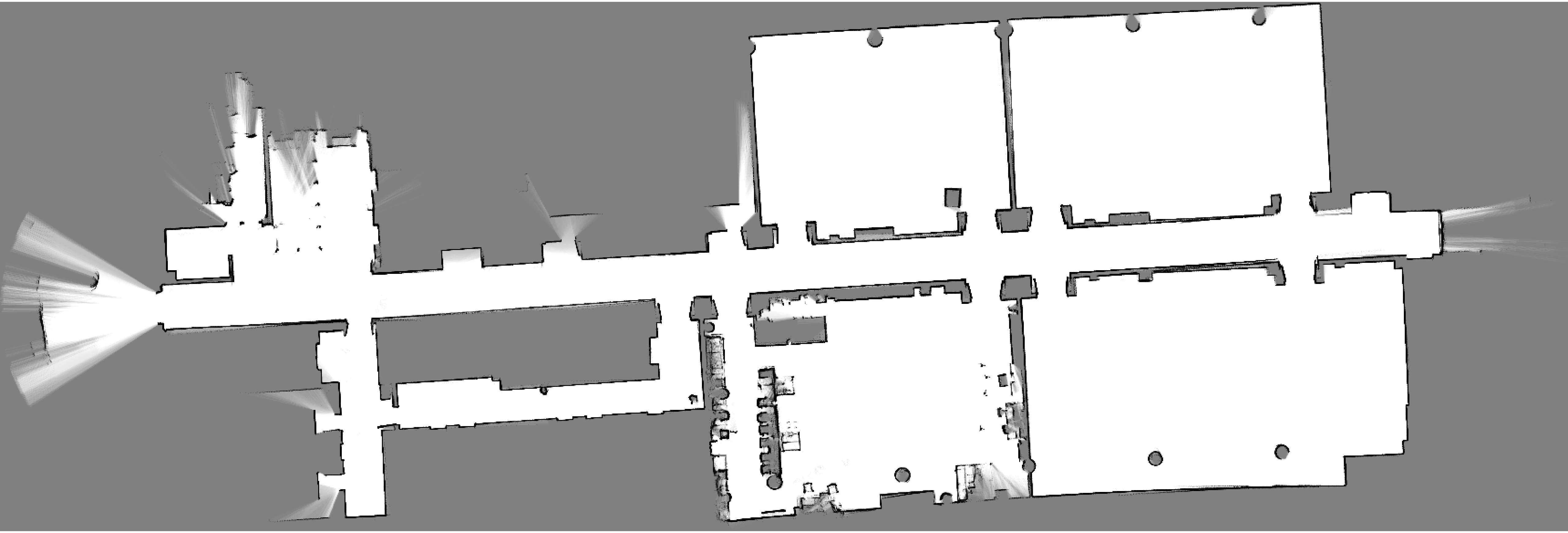
Configuration Space for a Mobile Robot

- Mobile robots operating on a flat ground (2D) have 3 DoF: (x, y, θ)
- Differential Drive: only two motors => only 2 degrees of freedom directly controlled (forward/ backward + turn) => non-holonomic
- Simplification: assume robot is holonomic and it is a point => configuration space is reduced to 2D (x,y)
- => inflate obstacle by size of the robot radius to avoid crashes => obstacle growing



Typical Configuration Space: Occupancy grid

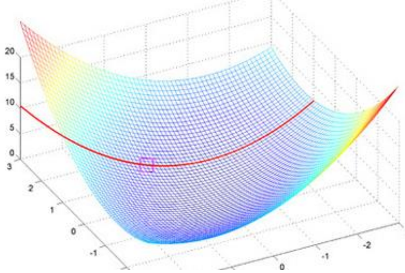
- Fixed cell decomposition: occupancy grid example: STAR Center



Path Planning: Overview of Algorithms

1. Optimal Control

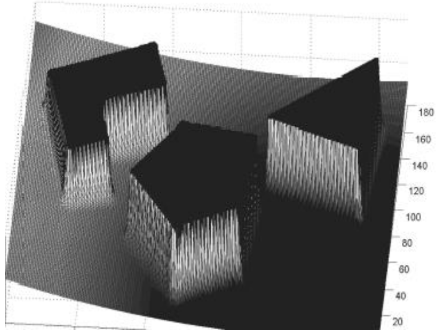
- Solves truly optimal solution
- Becomes intractable for even moderately complex as well as nonconvex problems



Source: http://mitocw.udsm.ac.tz

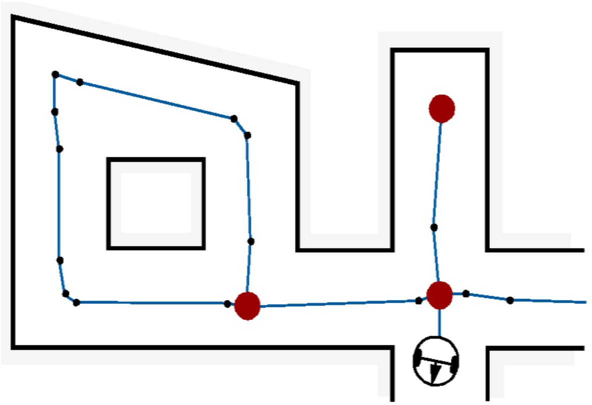
2. Potential Field

- Imposes a mathematical function over the state/configuration space
- Many physical metaphors exist
- Often employed due to its simplicity and similarity to optimal control solutions

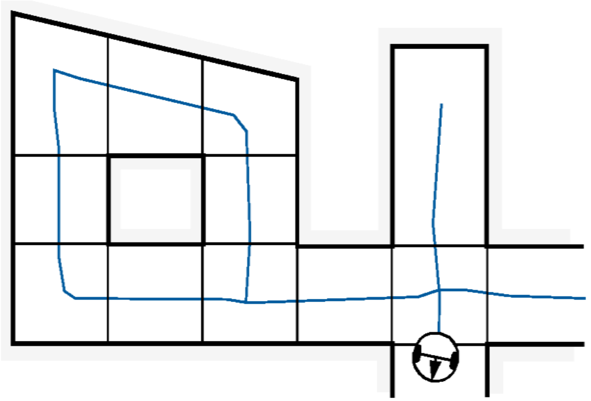


3. Graph Search

- Identify a set edges between nodes within the free space



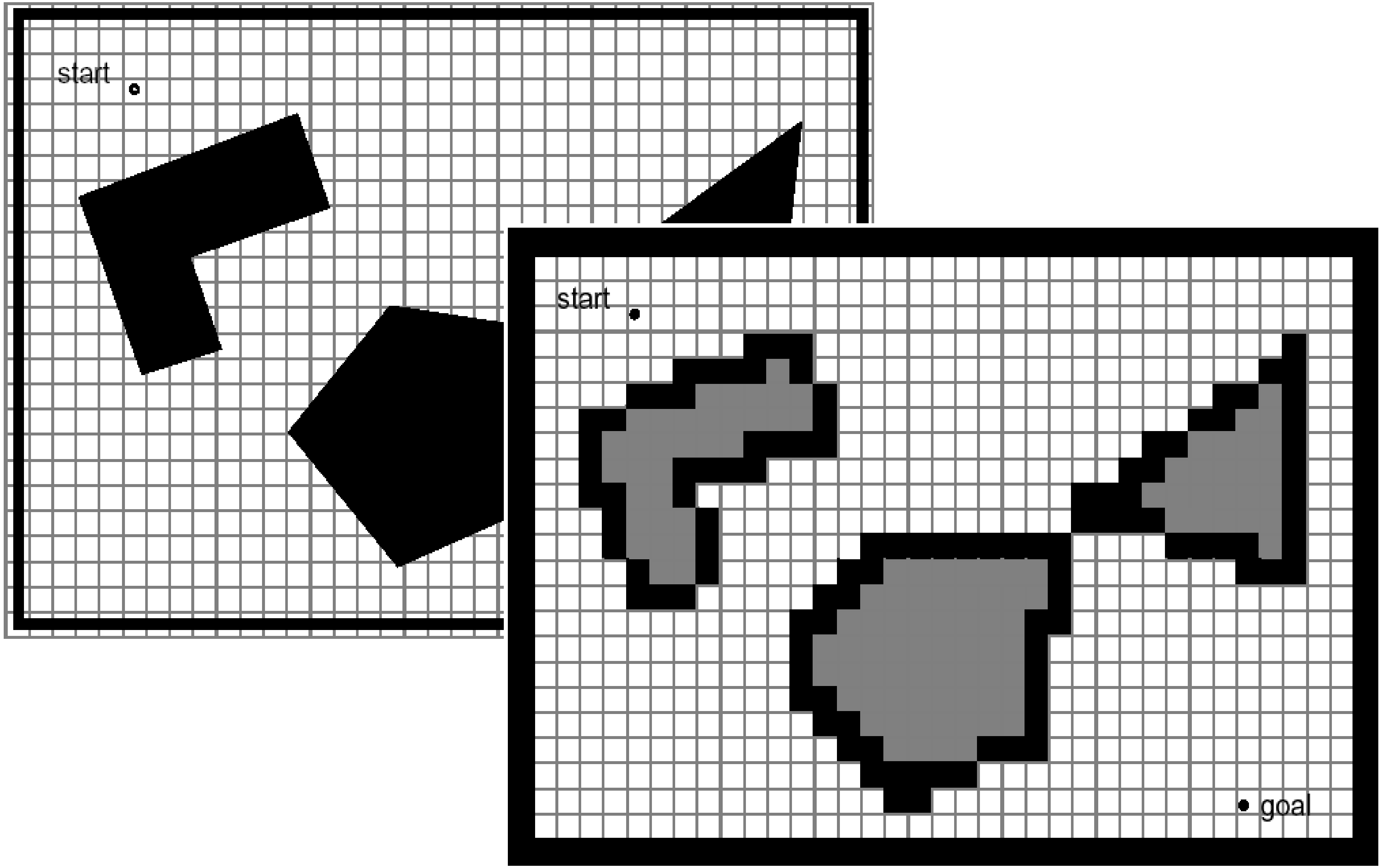
- Where to put the nodes?



Graph Search

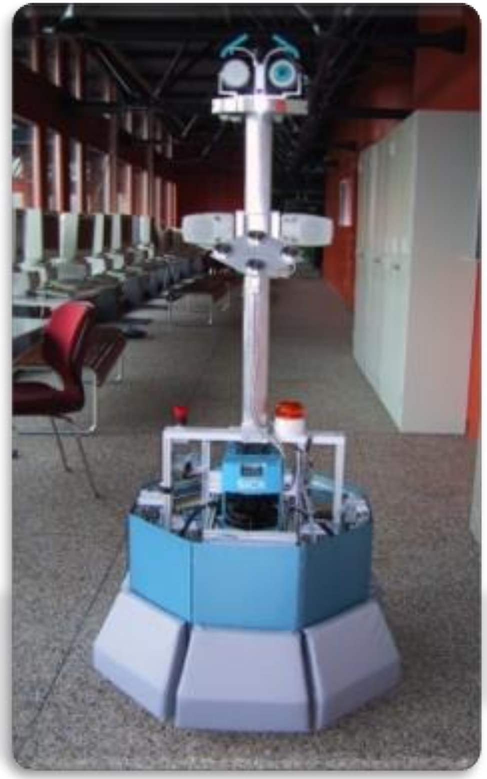
- Overview
  - Solves a least cost problem between two states on a (directed) graph
  - Graph structure is a discrete representation
- Limitations
  - State space is discretized → completeness is at stake
  - Feasibility of paths is often not inherently encoded
- Algorithms
  - (Preprocessing steps)
  - Breath first
  - Depth first
  - Dijkstra
  - A* and variants
  - D* and variants

Graph Construction: Cell Decomposition: Grid Map

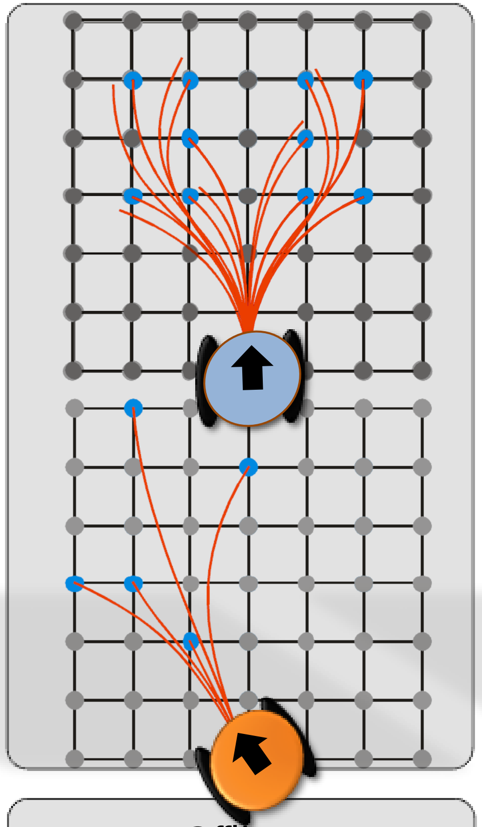


Graph Construction: State Lattice Design (1/2)

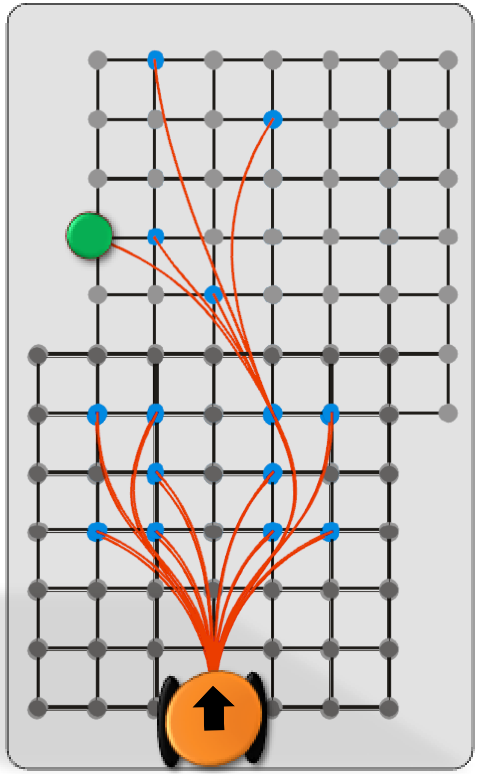
- Enforces edge feasibility
- Popular for Ackerman robots (e.g. cars)



Offline:
Motion Model



Offline:
Lattice Gen.

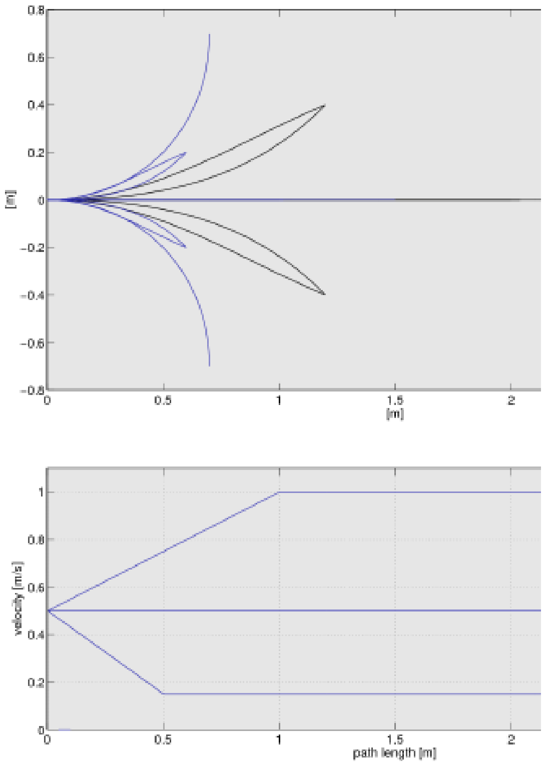


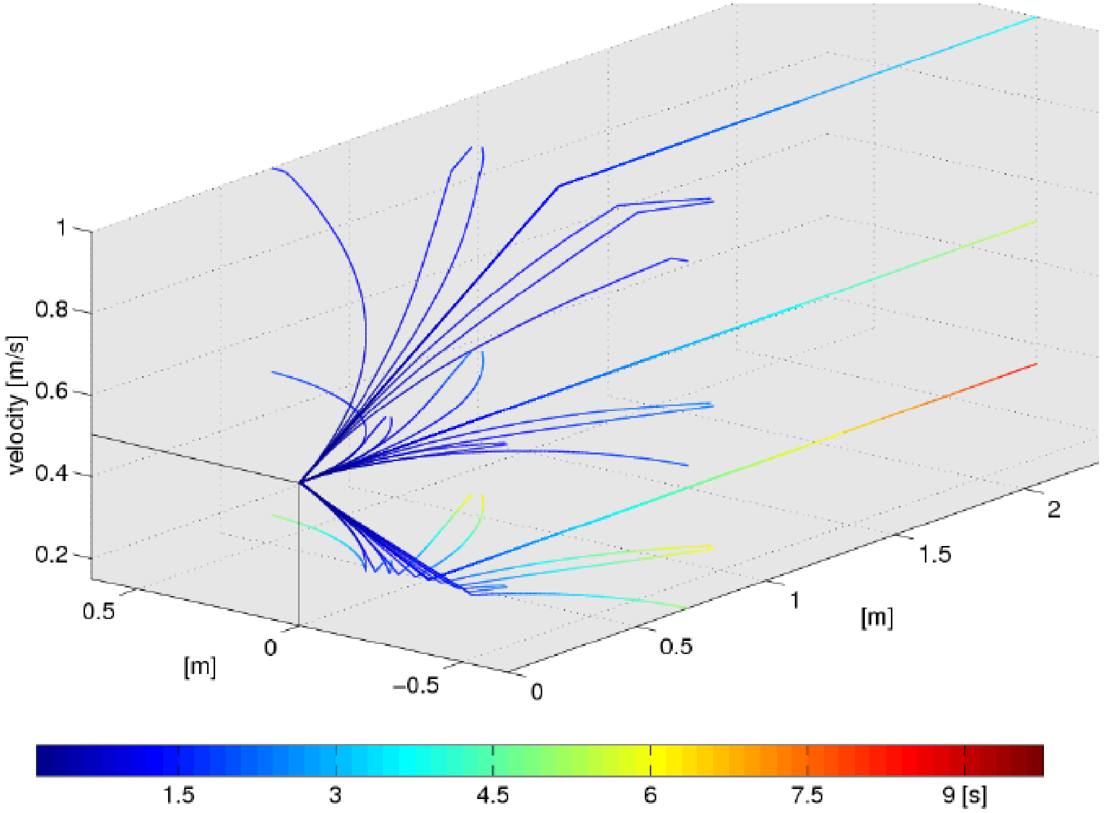
Online:
Incremental Graph
Constr.

Graph Construction: State Lattice Design (2/2)

Martin Rufli

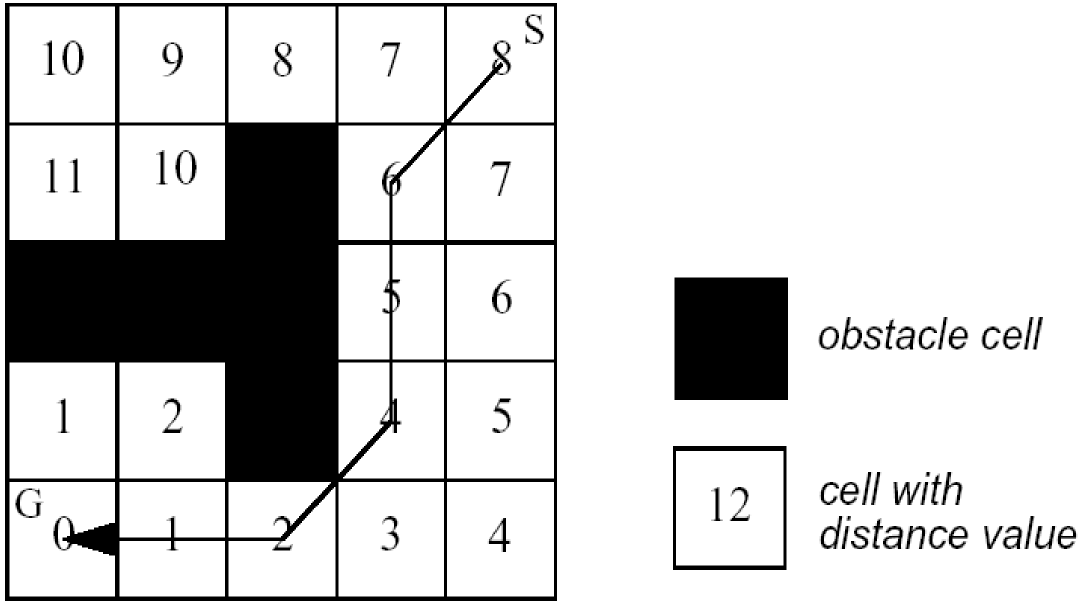
- State lattice encodes only kinematically feasible edges





Deterministic Graph Search

- Methods
  - Breath First
  - Depth First
  - **Dijkstra**
  - A* and variants
  - D* and variants
  - ...



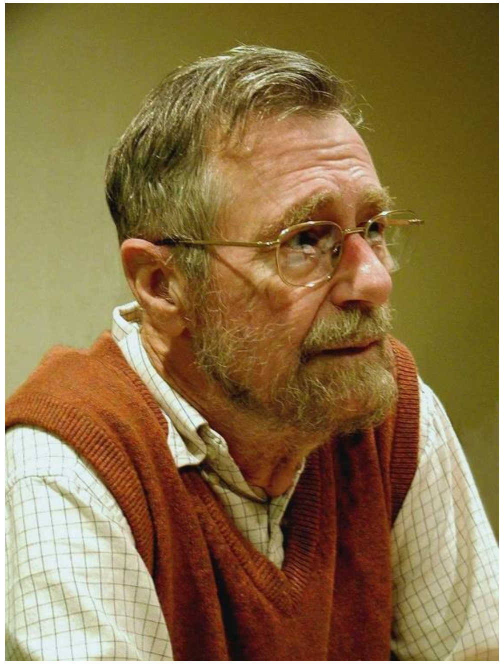
10	9	8	7	8 S
11	10	■	6	7
■	■	■	5	6
1	2	■	4	5
G 0	1	2	3	4

■ *obstacle cell*

12 *cell with distance value*

DIJKSTRA‘S ALGORITHM

EDSGER WYBE DIJKSTRA



1930 - 2002

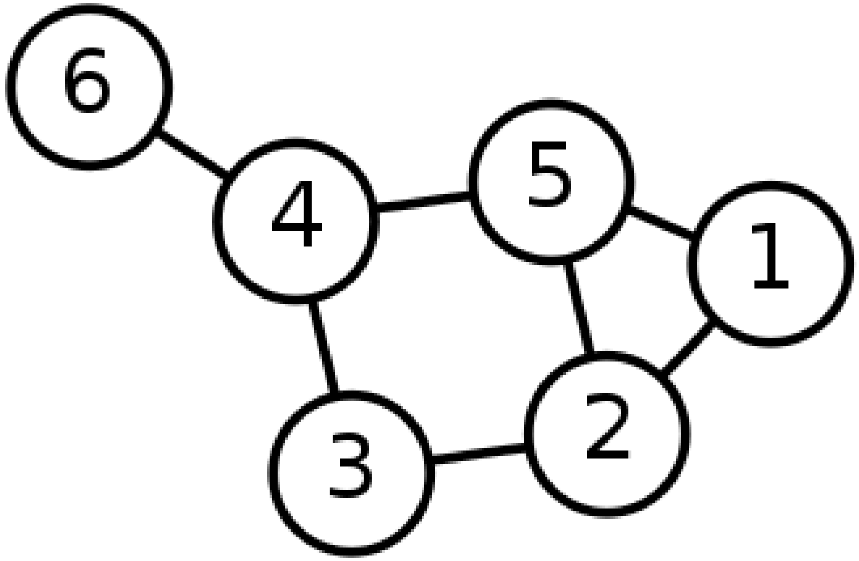
"Computer Science is no more about computers than astronomy is about telescopes."

http://www.cs.utexas.edu/~EWD/

SINGLE-SOURCE SHORTEST PATH PROBLEM

- **Single-Source Shortest Path Problem** - The problem of finding shortest paths from a source vertex *v* to all other vertices in the graph.

- **Graph**
- Set of vertices and edges
- Vertex:
  - Place in the graph; connected by:
- Edge: connecting two vertices
  - Directed or undirected (undirected in Dijkstra’s Algorithm)
  - Edges can have weight/ distance assigned



Dijkstra material from http://www.cs.utexas.edu/~tandy/barrera.ppt

Dijkstra's Algorithm

- Assign all vertices infinite distance to goal
- Assign 0 to distance from start
- Add all vertices to the queue

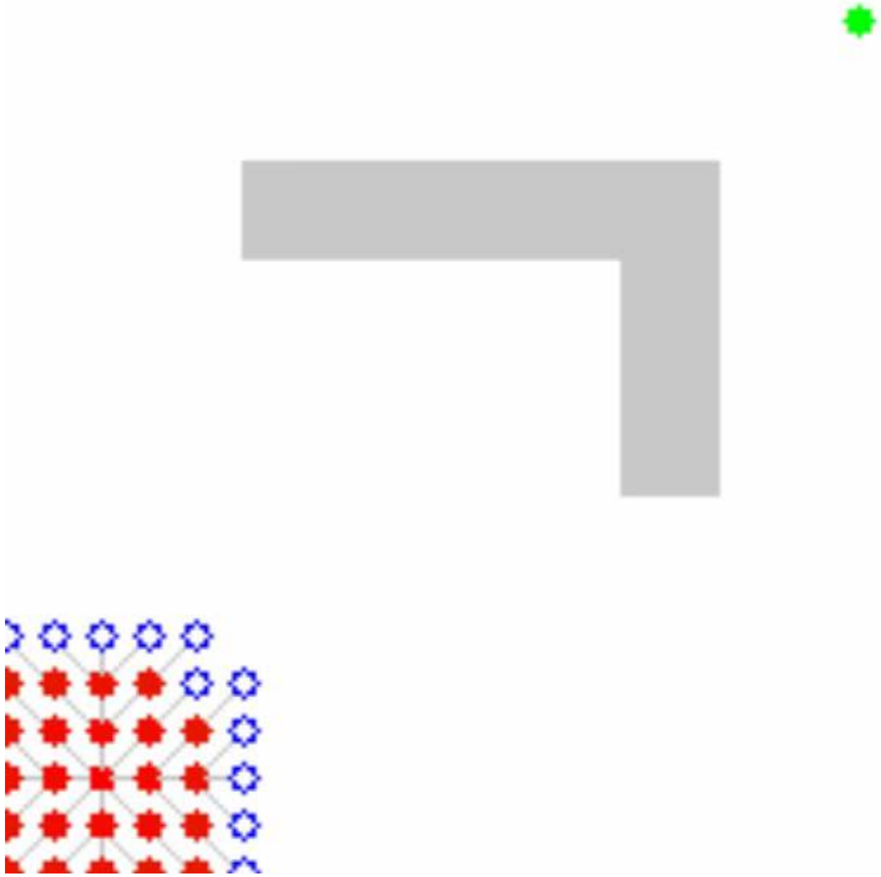
- While the queue is not empty:
  - Select vertex with smallest distance and remove it from the queue
  - Visit all neighbor vertices of that vertex,
  - calculate their distance and
  - update their (the neighbors) distance if the new distance is smaller

Dijkstra's Algorithm - Pseudocode

```
$dist[s] \leftarrow 0$                                (distance to source vertex is zero)
for all $v \in V - \{s\}$
      do $dist[v] \leftarrow \infty$                  (set all other distances to infinity)
$S \leftarrow \emptyset$                              (S, the set of visited vertices is initially empty)
$Q \leftarrow V$                                      (Q, the queue initially contains all vertices)
while $Q \neq \emptyset$                              (while the queue is not empty)
do   $u \leftarrow$ mindistance$(Q, dist)$            (select the element of Q with the min. distance)
     $S \leftarrow S \cup \{u\}$                      (add u to list of visited vertices)
     for all $v \in neighbors[u]$
          do if   $dist[v] > dist[u] + w(u, v)$              (if new shortest path found)
                  then    $d[v] \leftarrow d[u] + w(u, v)$   (set new value of shortest path)
          (if desired, add traceback code)
return $dist$
```

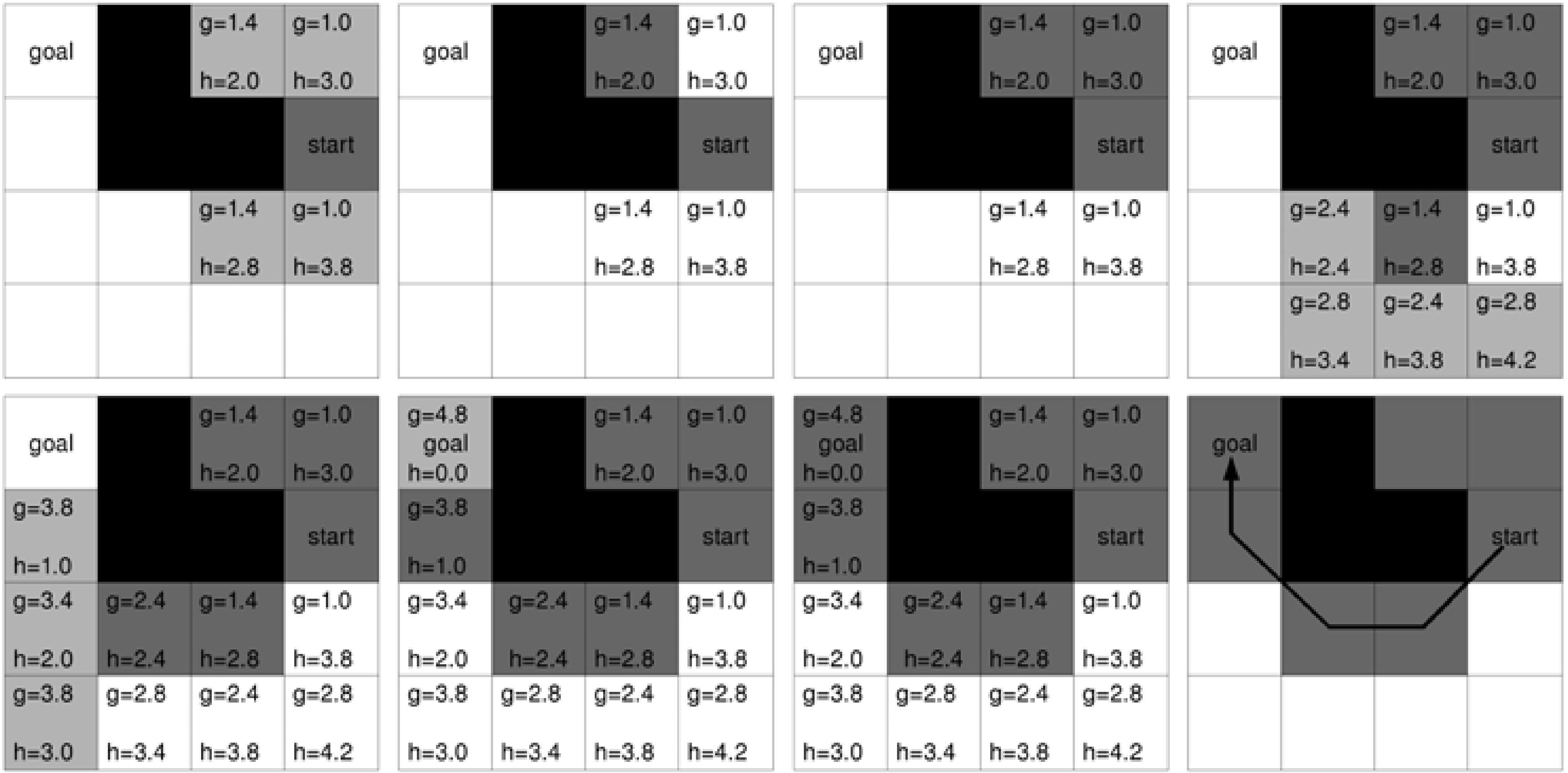
Dijkstra’s Algorithm for Path Planning: Grid Maps

- Graph:
  - Neighboring free cells are connected:
    - 4-neighborhood: up/ down/ left right
    - **8-neighborhood**: also diagonals
  - All edges have weight 1
- Stop once goal vertex is reached
- Per vertex: save edge over which the shortest distance from start was reached => Path



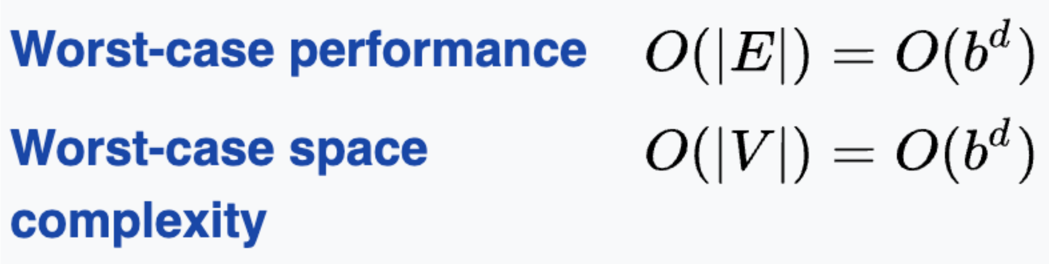
Graph Search Strategies: A* Search

- Similar to Dijkstra‘s algorithm, except that it uses a heuristic function h(n)
- f(n) = g(n) + h(n)



A*

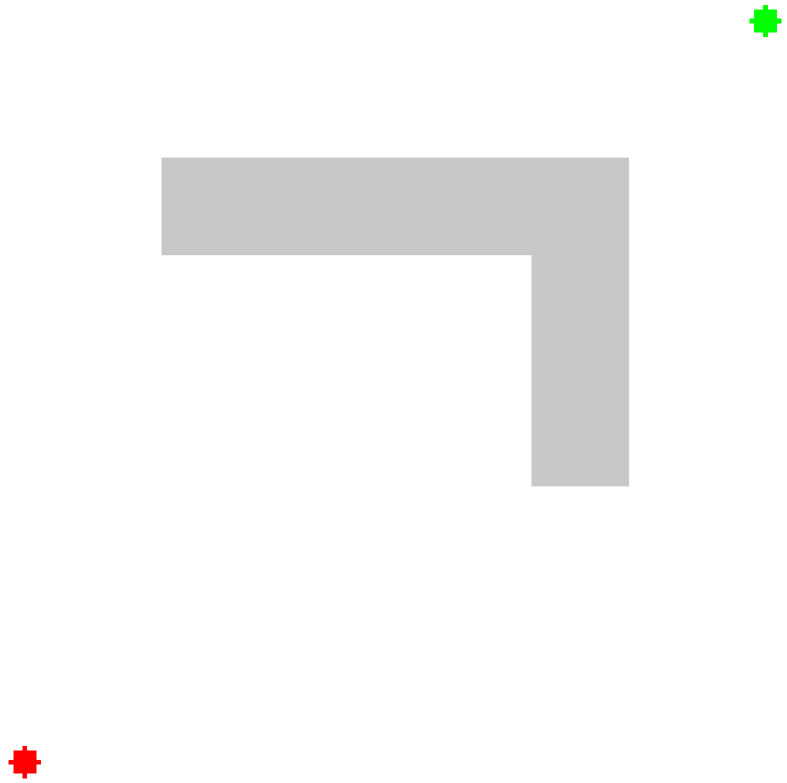
- Developed 1986 as part of the Shakey project!
- Complexity:

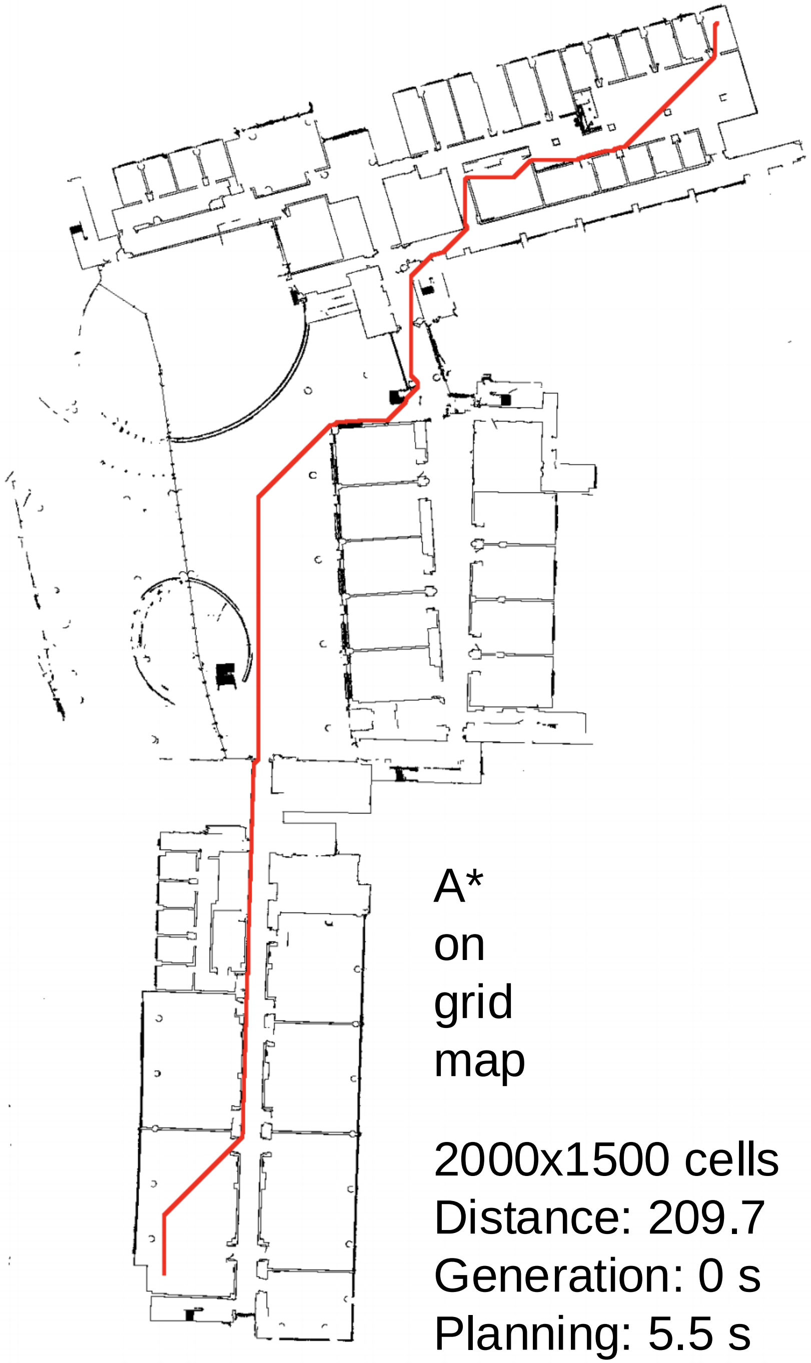


Worst-case performance	$O(\|E\|) = O(b^d)$
Worst-case space complexity	$O(\|V\|) = O(b^d)$

b: branching factor
d: depth

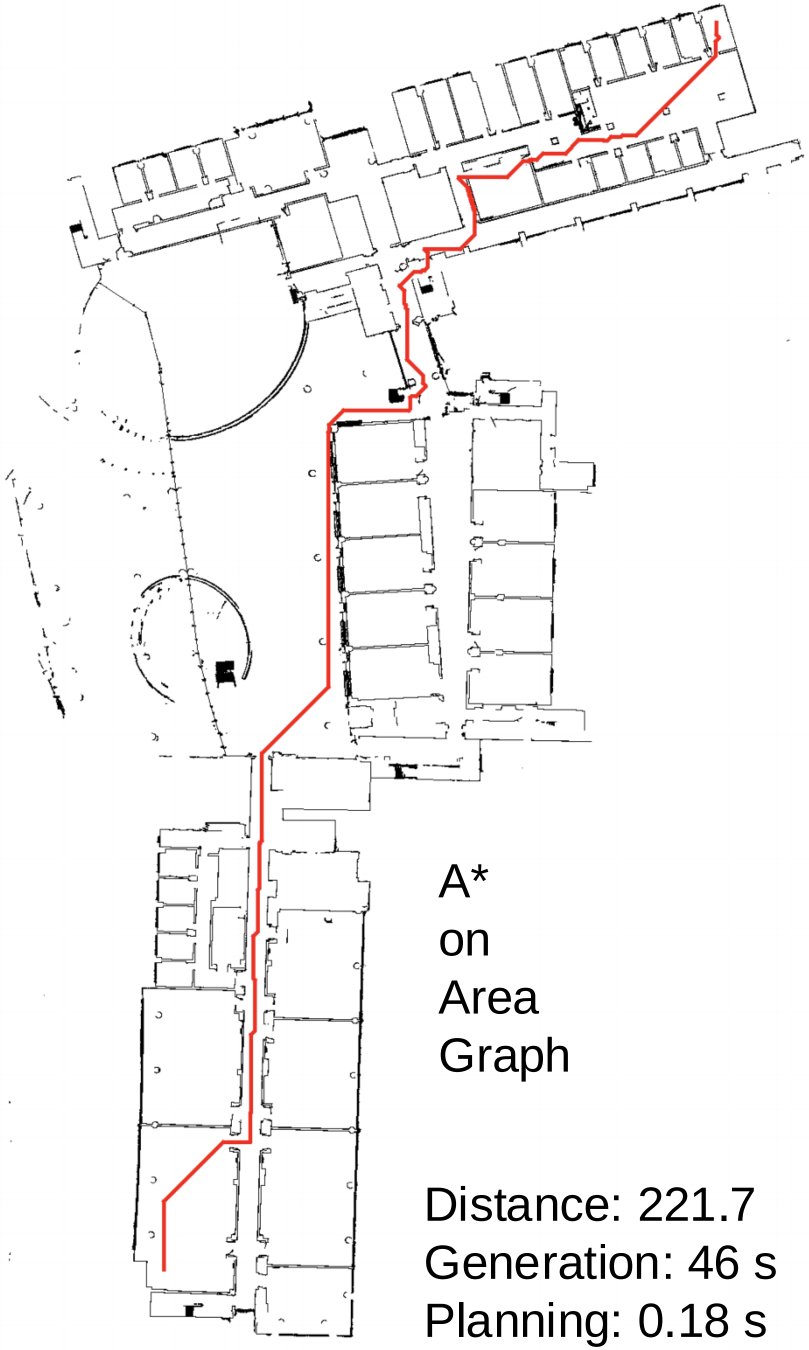
- Good heuristic => small branching factor





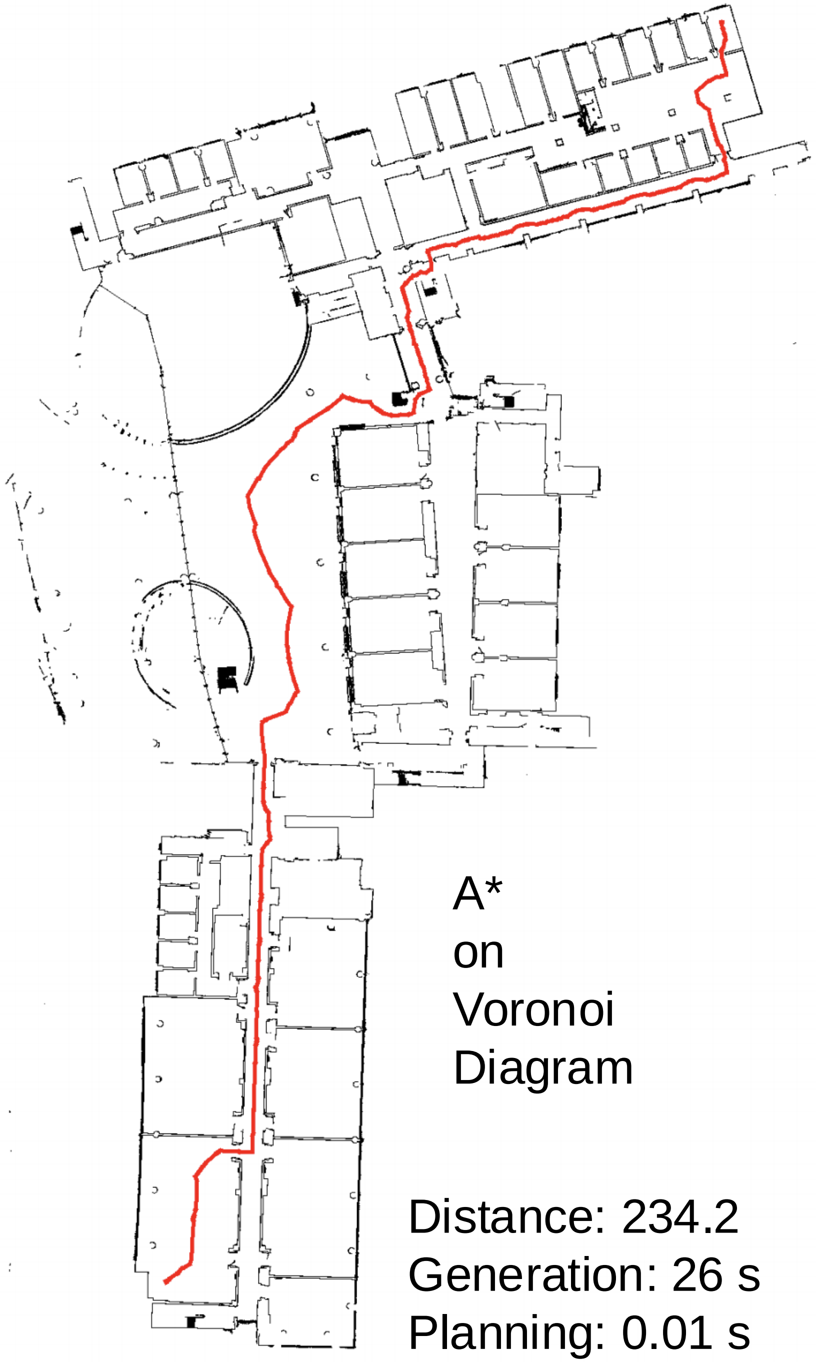
A*
on
grid
map

2000x1500 cells
Distance: 209.7
Generation: 0 s
Planning: 5.5 s



A*
on
Area
Graph

Distance: 221.7
Generation: 46 s
Planning: 0.18 s



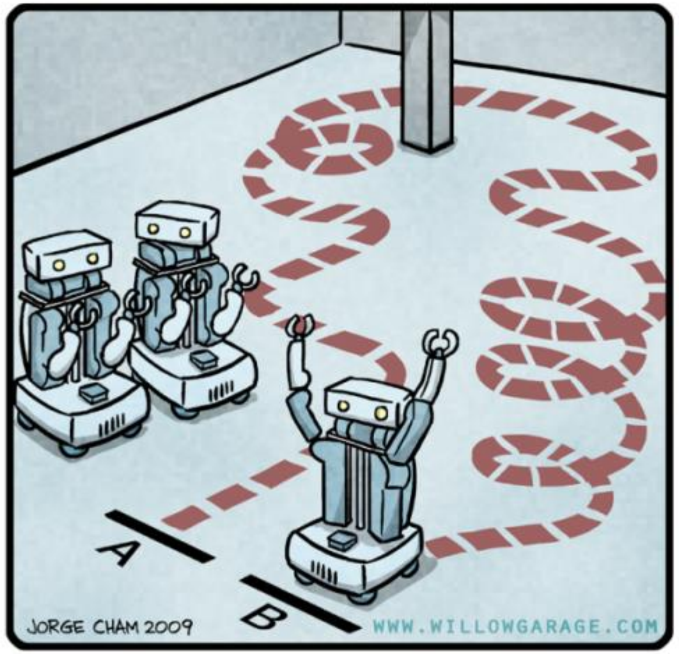
A*
on
Voronoi
Diagram

Distance: 234.2
Generation: 26 s
Planning: 0.01 s

ROS Navigation

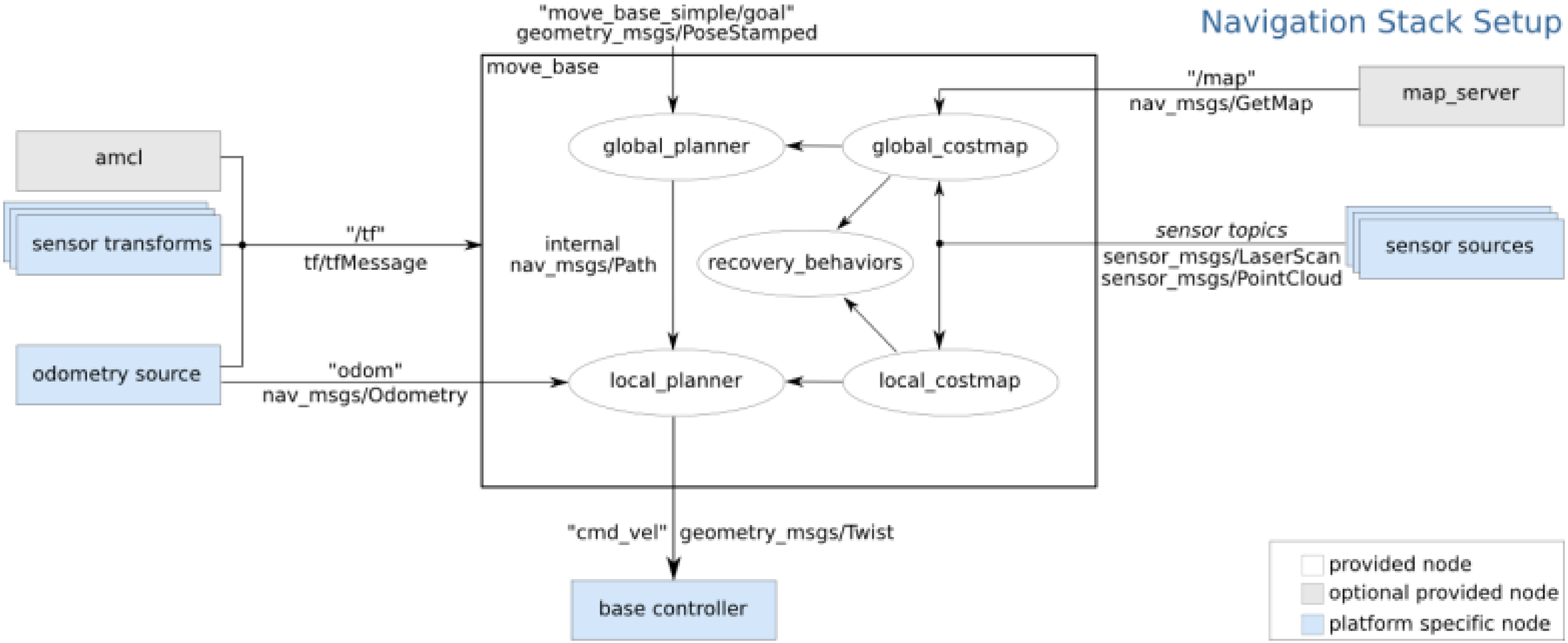
- http://wiki.ros.org/navigation

R.O.B.O.T. Comics



"HIS PATH-PLANNING MAY BE SUB-OPTIMAL, BUT IT'S GOT FLAIR."

Path Planning in ROS: move_base



technische universität
dortmund

teb_local_planner

An optimal trajectory planner for mobile robots based on Timed-Elastic-Bands

http://wiki.ros.org/teb_local_planner

ROS