Search-Based Footstep Planning

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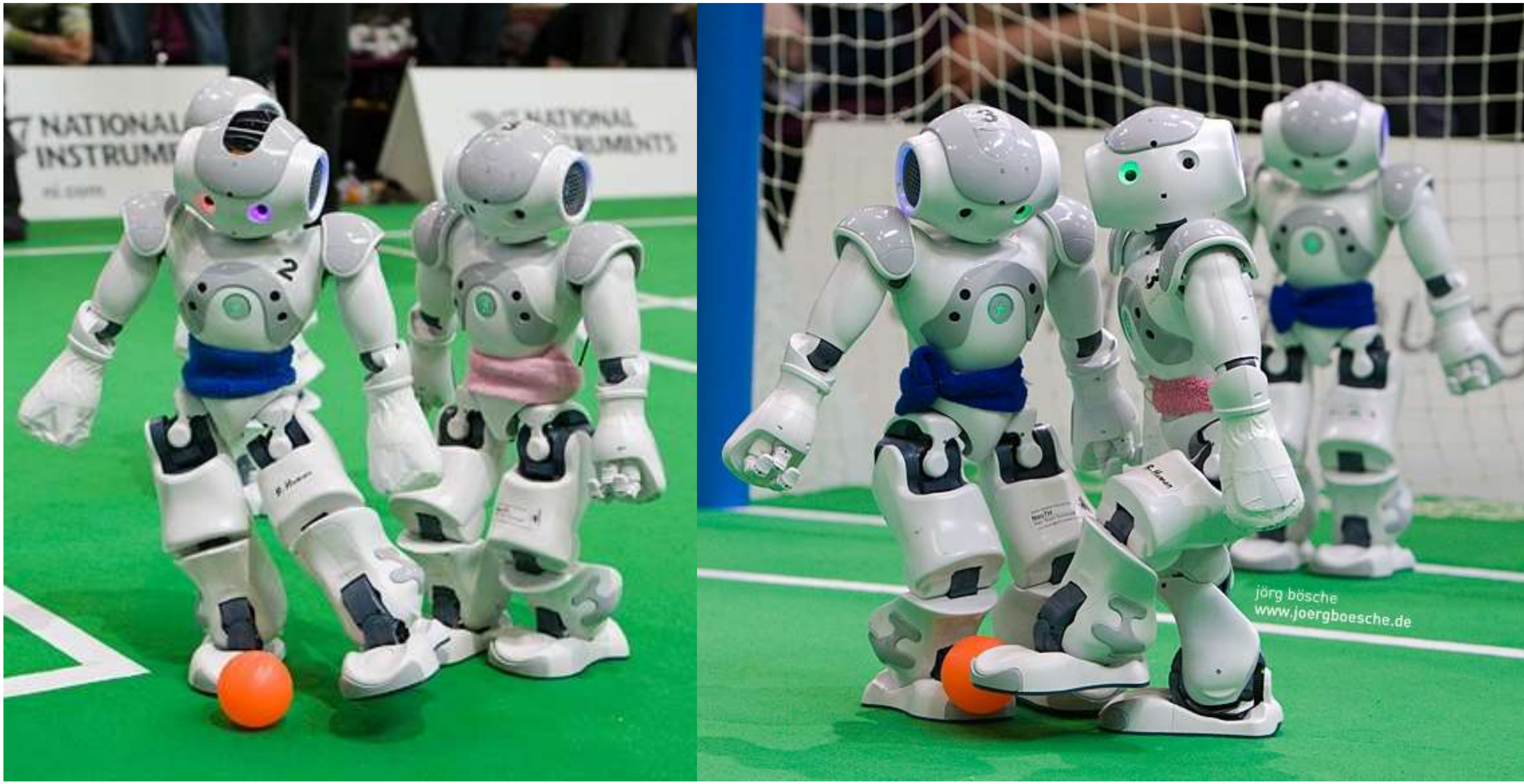
Motivation



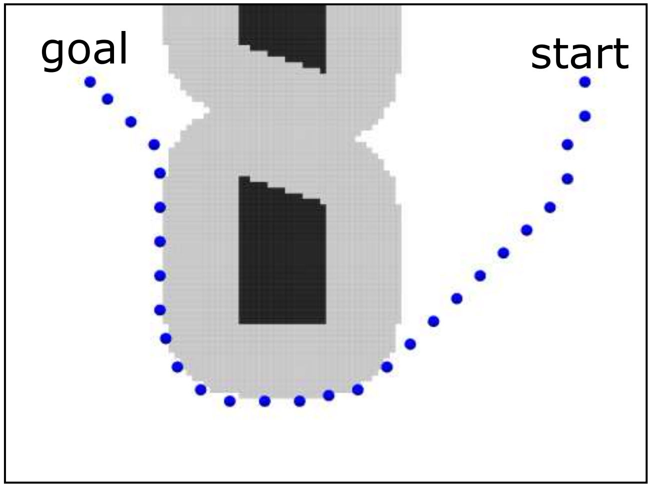
BHuman vs. Nimbro, RoboCup German Open 2010

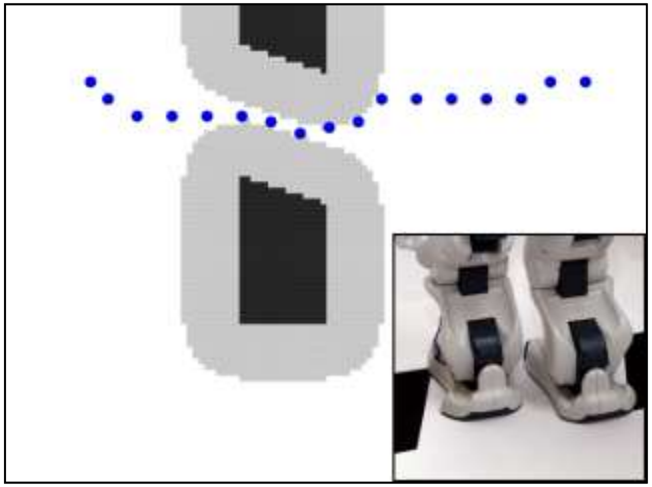
Photo by J. Bösche, www.joergboesche.de

Previous approaches: 2D Path Planning

- Compute collision-free 2D path first, then footsteps in a local area
  [Li et al. '03, Chestnutt & Kuffner '04]

- Problem: 2D planner cannot consider all capabilities of the robot



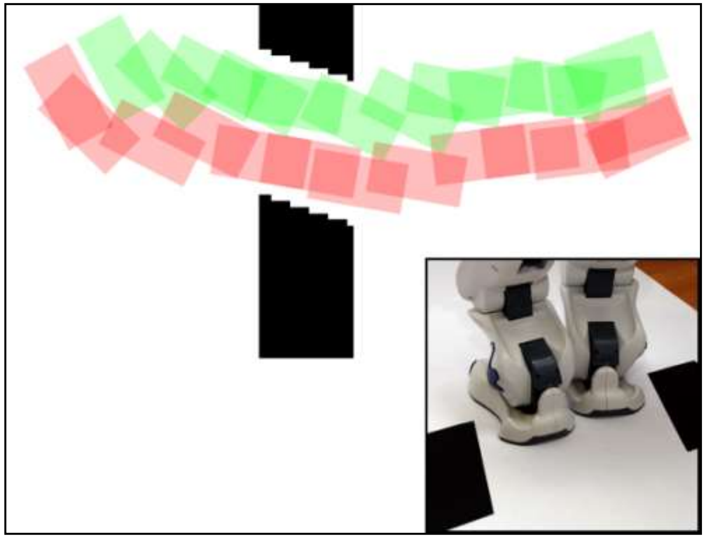


Path Planning for Humanoids

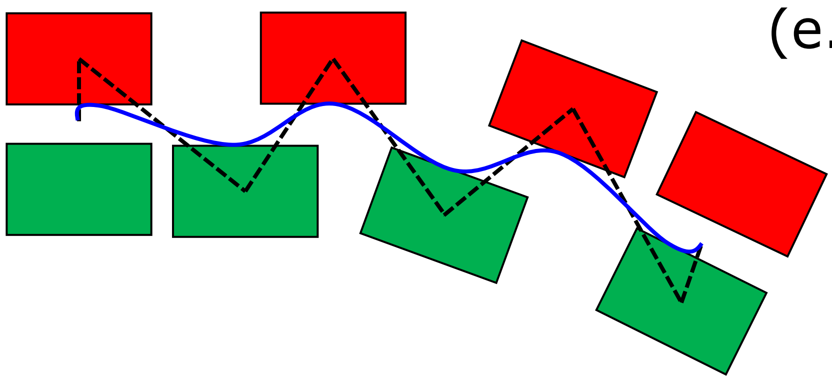
- Humanoids can avoid obstacles by stepping over or close to them
- However, planning whole-body motions has a high computational complexity

[Hauser et al. ‘07, Kanoun ’10, …]

- Planning for possible foot locations reduces the problem



Overview: Path Planning for Humanoids



Footsteps

↓

Desired ZMP Trajectory

↓

CoM Trajectory

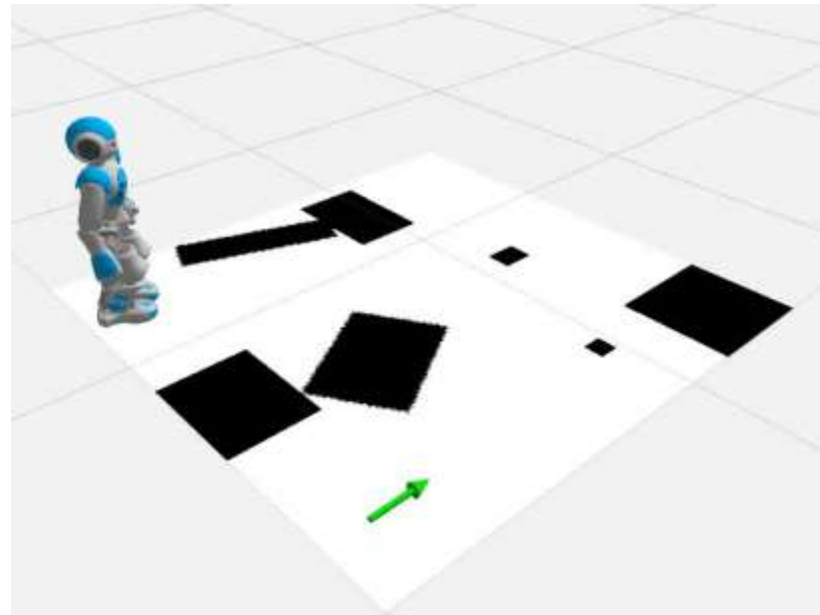
↓

Joint Angles

Pattern Generator (e.g. Kajita et al. 2003)

Footstep planning with A*

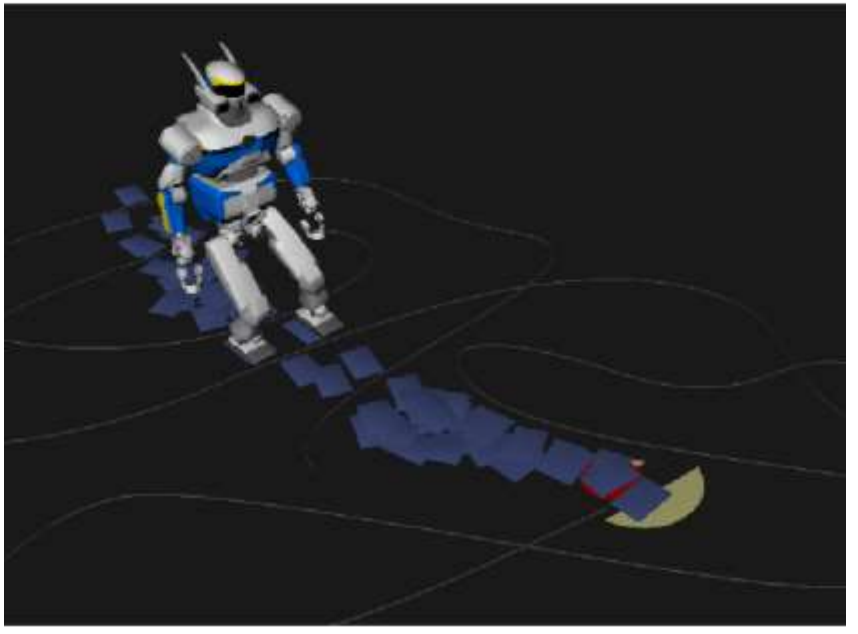
- Search space: (x,y,θ)
- Discrete set of footsteps
- Optimal solution with A*



[Kuffner '01, Chestnutt et al. '05, '07]

Randomized Footstep Planning

- Search space of footstep actions with RRT / PRM
- Fast planning results
- Enables high number of actions
- No guarantees on optimality or completeness

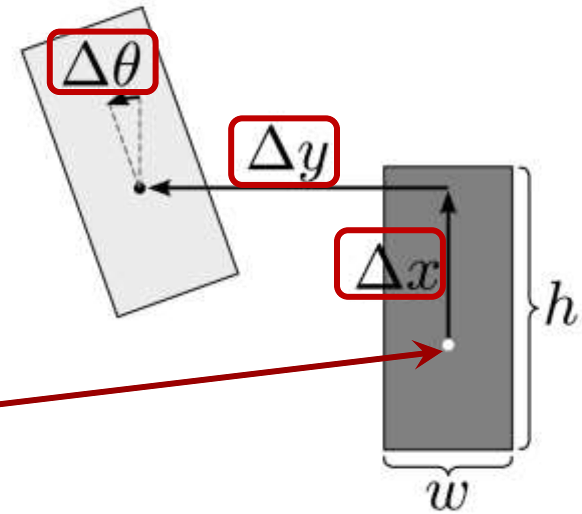


[Perrin et al. '11]

A* Heuristic Search

- Best-first search to find a cost-optimal path to a goal state
- Expands states according to the evaluation function $f(s)=g(s)+h(s)$
- $g(s)$: Costs from start to current state
- $h(s)$: Heuristic, estimated costs to the goal
- Heuristic must be admissible: it may never overestimate the costs to the goal

Footstep Planning



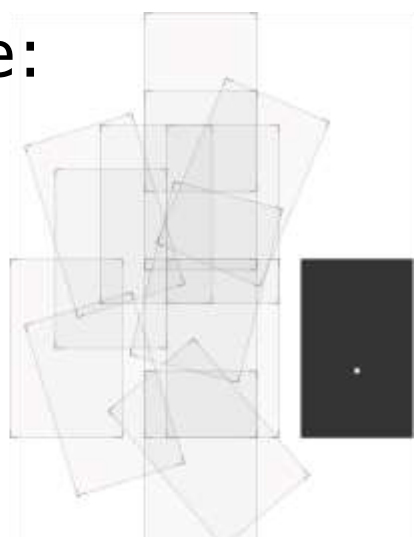
- State $s = (x, y, \theta)$
- Footstep action $a = (\Delta x, \Delta y, \Delta\theta)$
- Fixed set of footstep actions $F = \{a_1, \ldots, a_n\}$
- Successor state $s' = t(s, a)$
- Transition costs reflect execution time:

$$c(s, s') = \|(\Delta x, \Delta y)^\top\| + k + d(s')$$

Euclidean distance

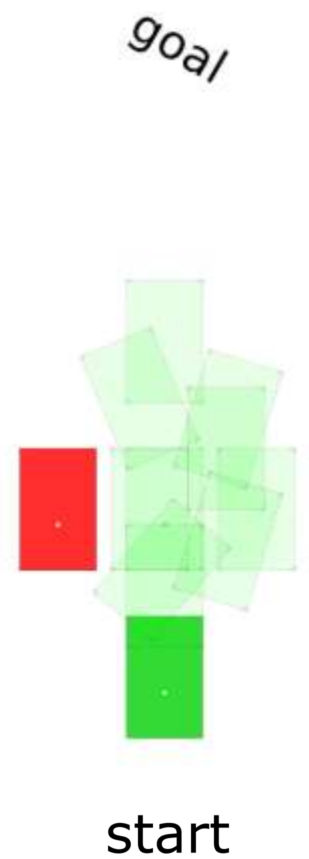
constant step cost

costs based on the distance to obstacles

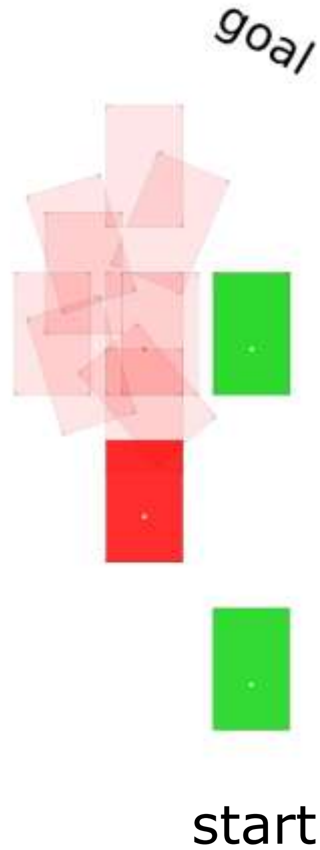


Footstep Planning

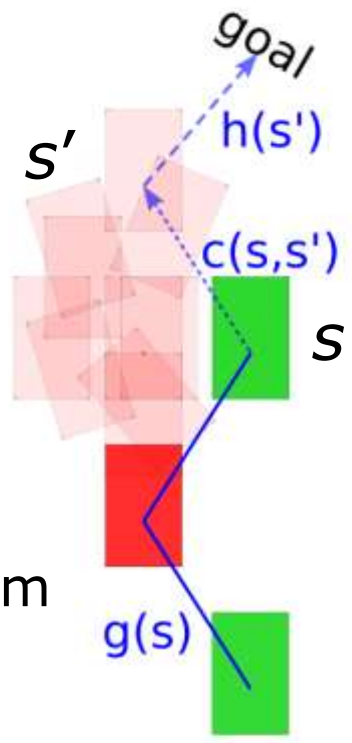
Footstep Planning



Footstep Planning



Footstep Planning



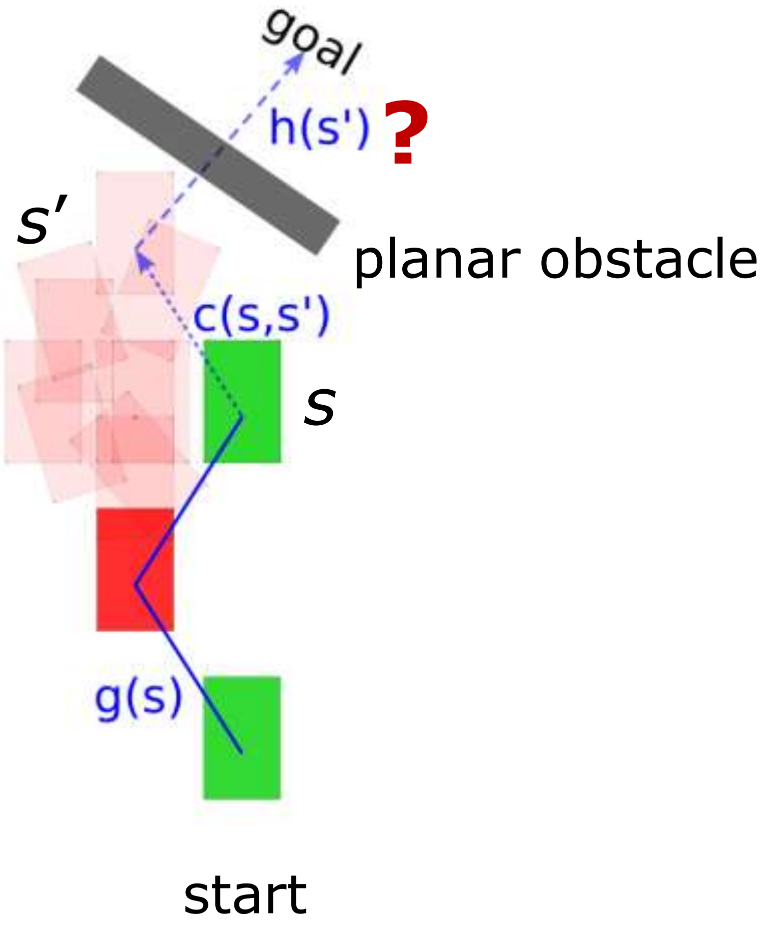
estimated costs from *s*′ to goal

transition costs

path costs from start to *s*

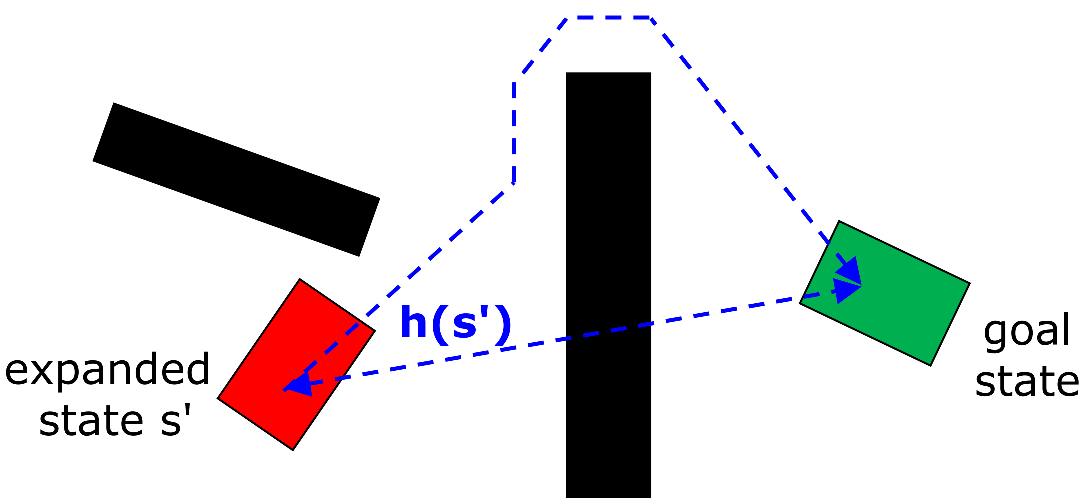
start

Footstep Planning



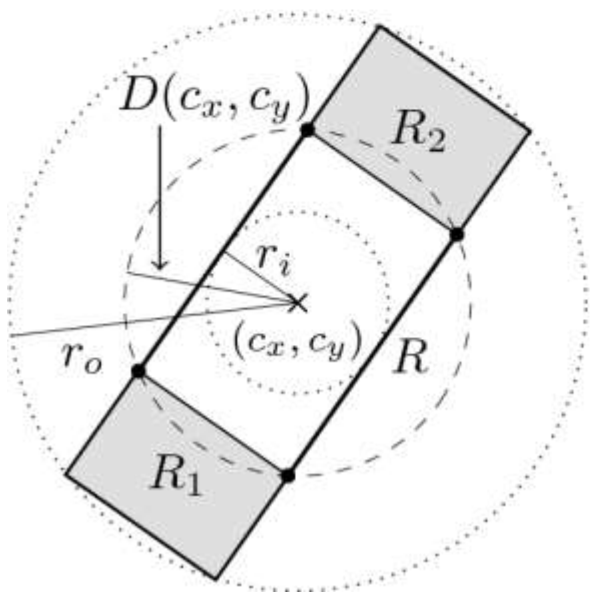
Heuristic

- Estimates the costs to the goal
- Critical for planner performance
- Usual choices:
  - Euclidean distance
  - 2D Dijkstra path



Collision Checking in 2D

- Footprint is rectangular with arbitrary orientation
- Evaluating the distance between foot center and the closest obstacle may not yield correct or optimal results
- Recursively subdivide footstep shape

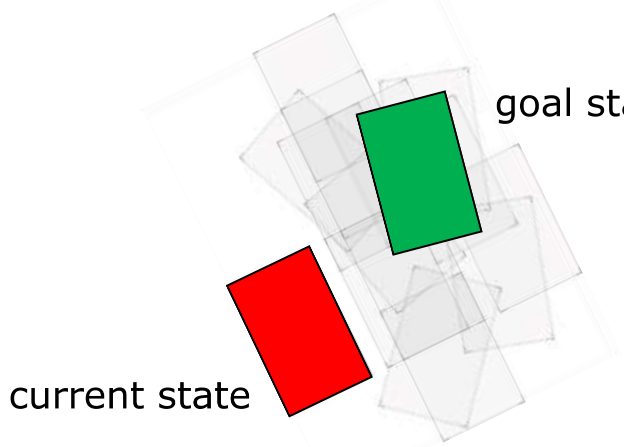


$D(c_x, c_y)$ = distance to the closest obstacle (precomputed map)

[Sprunk et al. (ICRA '11)]

Search-Based Footstep Planning

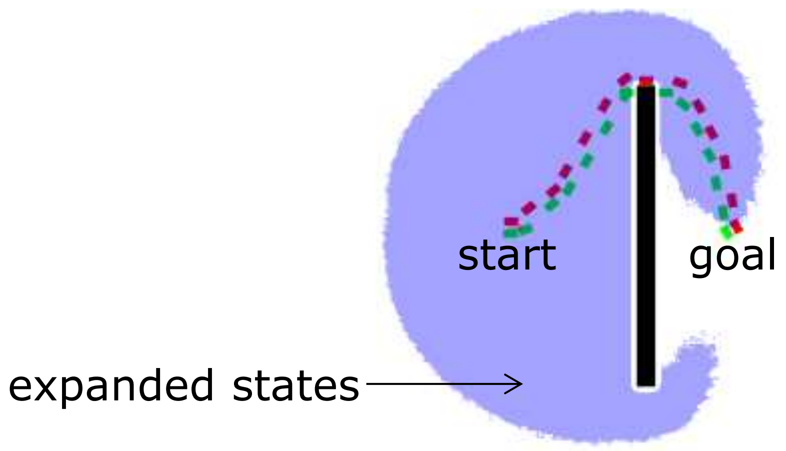
- Concatenation of footstep actions builds a lattice in the global search space
- Only valid states after a collision check are added
- Goal state may not be exactly reached, but it is sufficient to reach a state close by (within the motion range)



Search-Based Footstep Planning

- We can now apply heuristic search methods on the state lattice
- Search-based planning library: www.ros.org/wiki/sbpl
- Footstep planning implementation based on SBPL: www.ros.org/wiki/footstep_planner

Local Minima in the Search Space



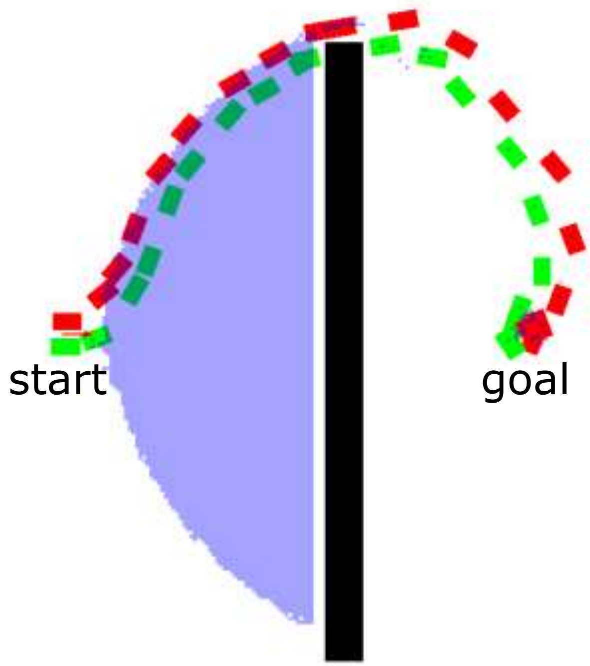
- A* will search for the optimal result
- Initially sub-optimal results are often sufficient for navigation
- Provable sub-optimality instead of randomness yields more efficient paths

Anytime Repairing A* (ARA*)

- Heuristic inflation by a factor w allows to efficiently deal with local minima: weighted A* (wA*)
- ARA* runs a series of wA* searches, iteratively lowering w as time allows
- Re-uses information from previous iterations

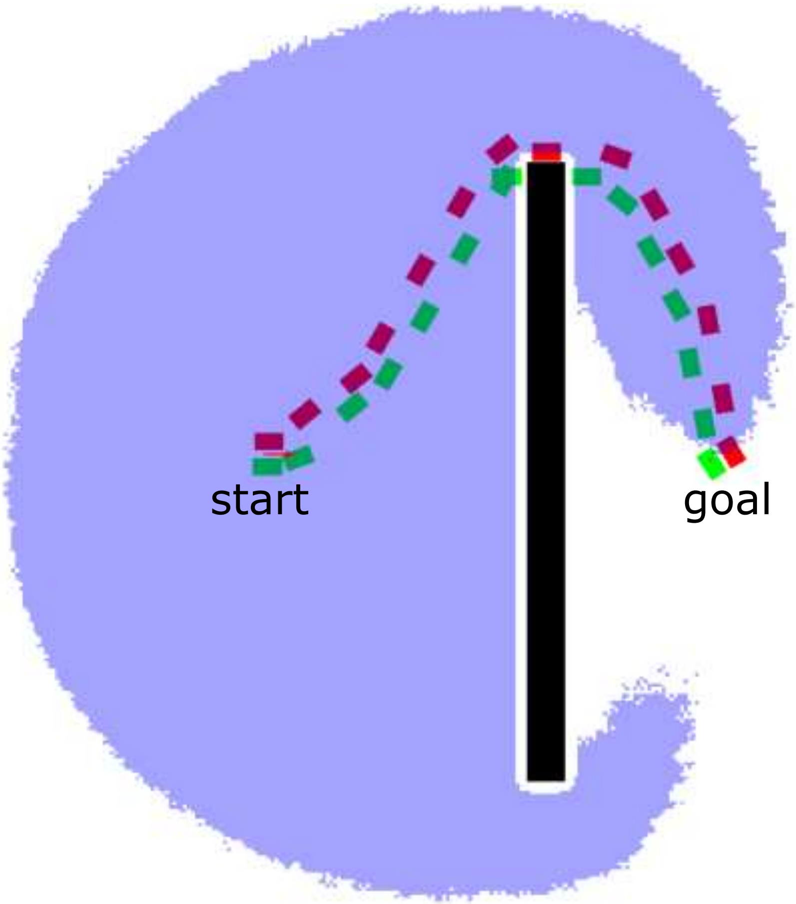
[Likhachev et al. (NIPS 2004), Hornung et al. (Humanoids 2012)]

ARA* with Euclidean Heuristic



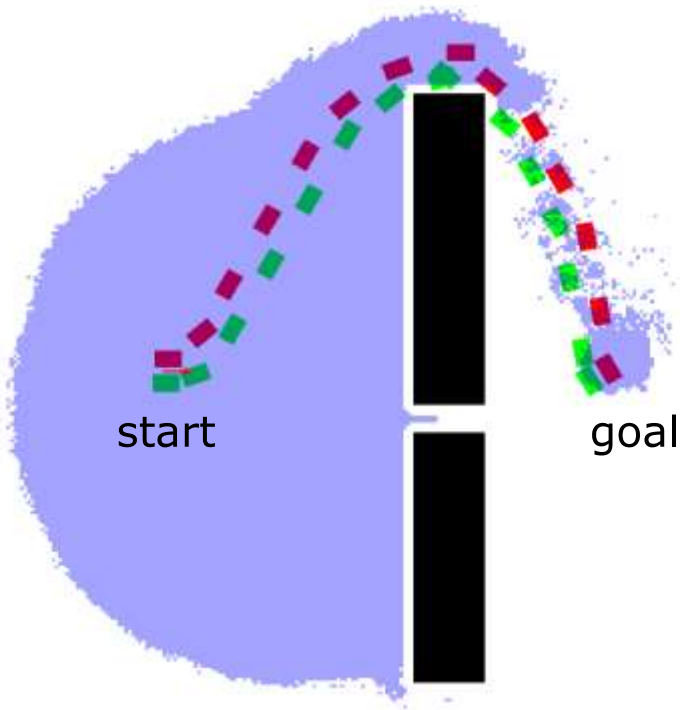
w = 10

ARA* with Euclidean Heuristic



w = 1

ARA* with Dijkstra Heuristic

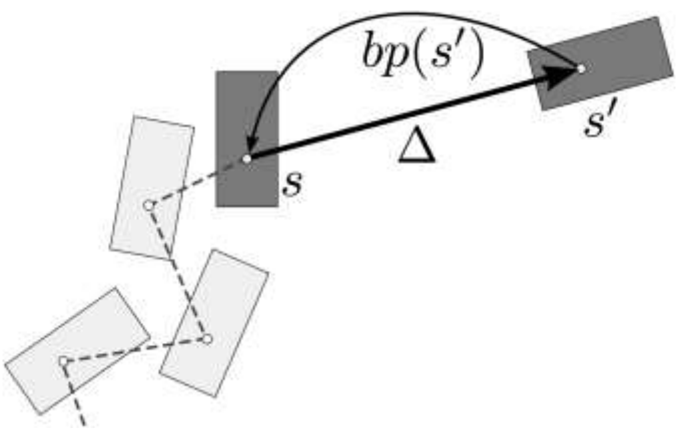


w = 1

Performance depends on well-designed heuristic

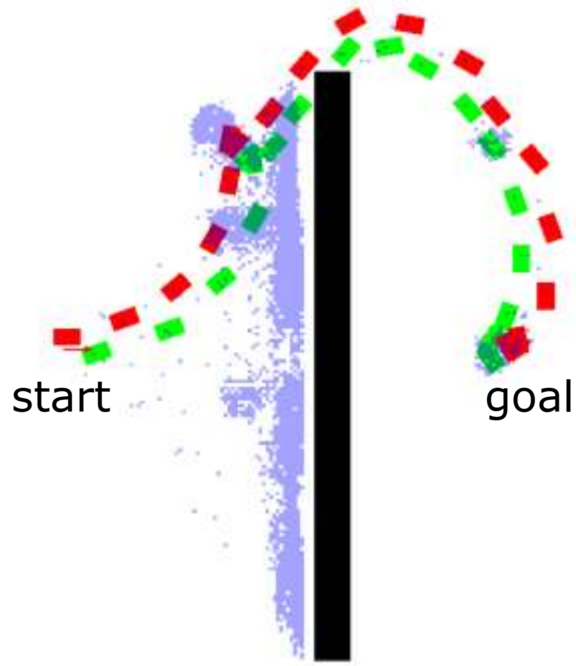
Randomized A* (R*)

- Iteratively constructs a graph of sparsely placed randomized sub-goals (exploration)
- Plans between sub-goals with wA*, preferring easy-to-plan sequences
- Iteratively lowers w as time allows



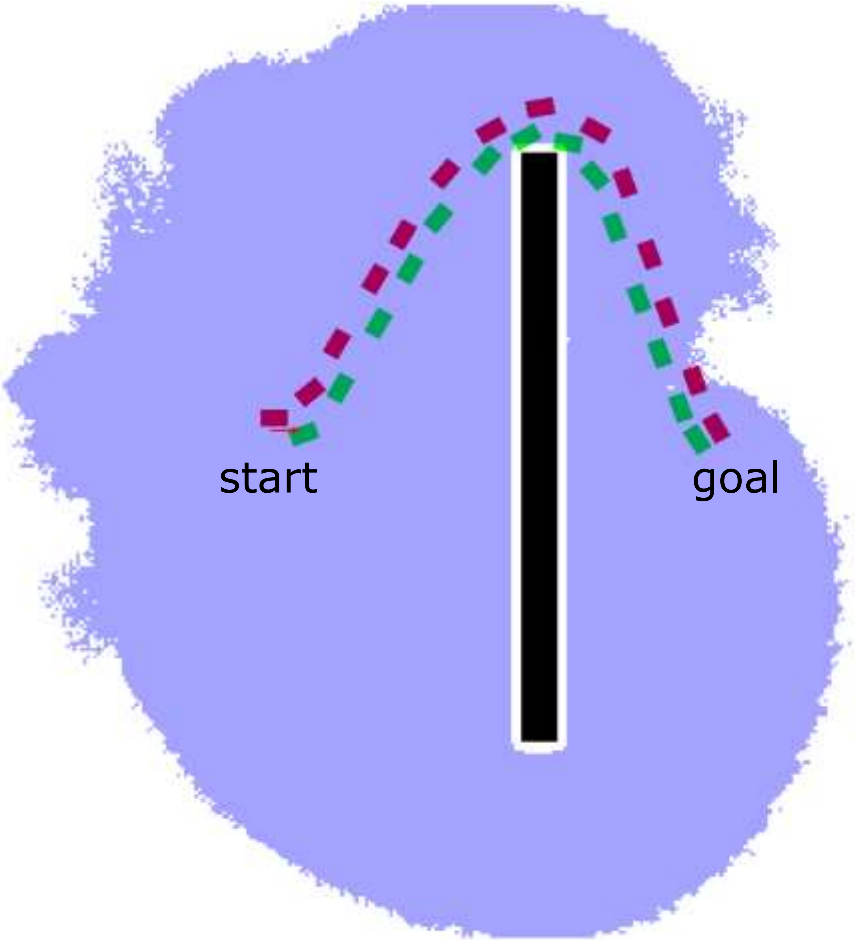
[Likhachev & Stentz (AAAI 2008), Hornung et al. (Humanoids 2012)]

R* with Euclidean Heuristic



w = 10

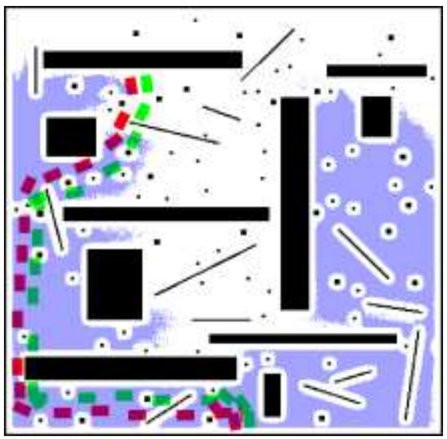
R* with Euclidean Heuristic



w = 1

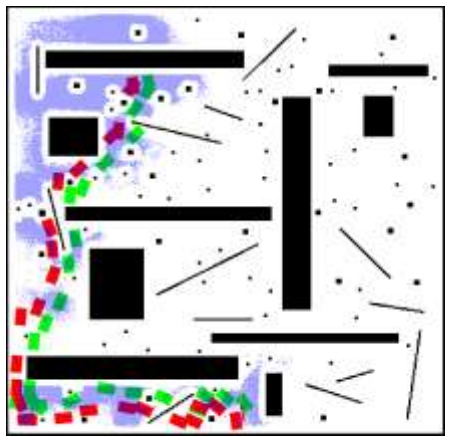
Planning in Dense Clutter Until First Solution

A*
Euclidean heur.



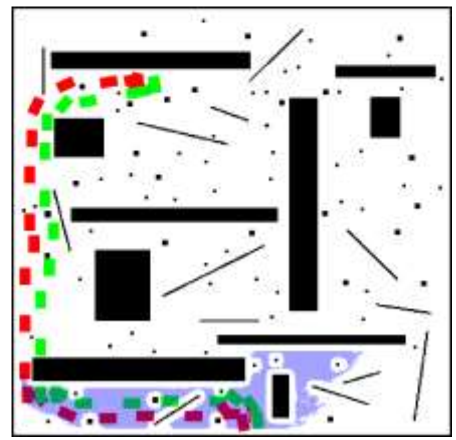
11.9 sec.

R*
Euclidean heur.



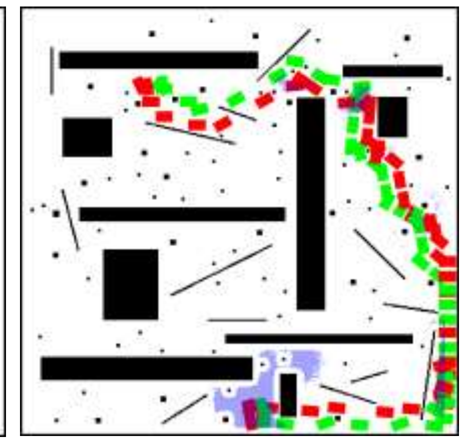
0.4 sec.

ARA*
Euclidean heur.



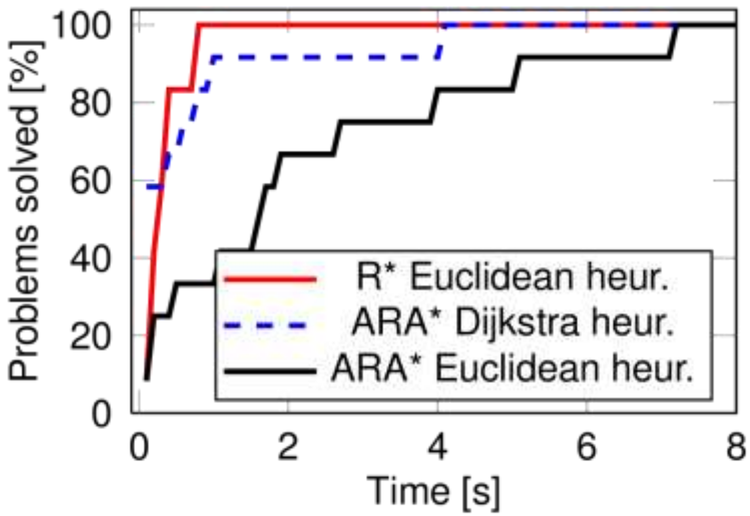
2.7 sec.

ARA*
Dijkstra heur.



0.7 sec.

Planning in Dense Clutter Until First Solution



Planner	Heuristic	Planning time [s]	Path costs
R* (w=5)	Euclidean	0.32 ± 0.23	16.45 ± 3.16
ARA* (w=5)	Euclidean	2.15 ± 2.21	13.57 ± 1.15
ARA* (w=5)	2D Dijkstra	0.56 ± 1.13	20.41 ± 5.08
A* (w=1)	Euclidean	33.31 ± 15.00	11.06 ± 1.20

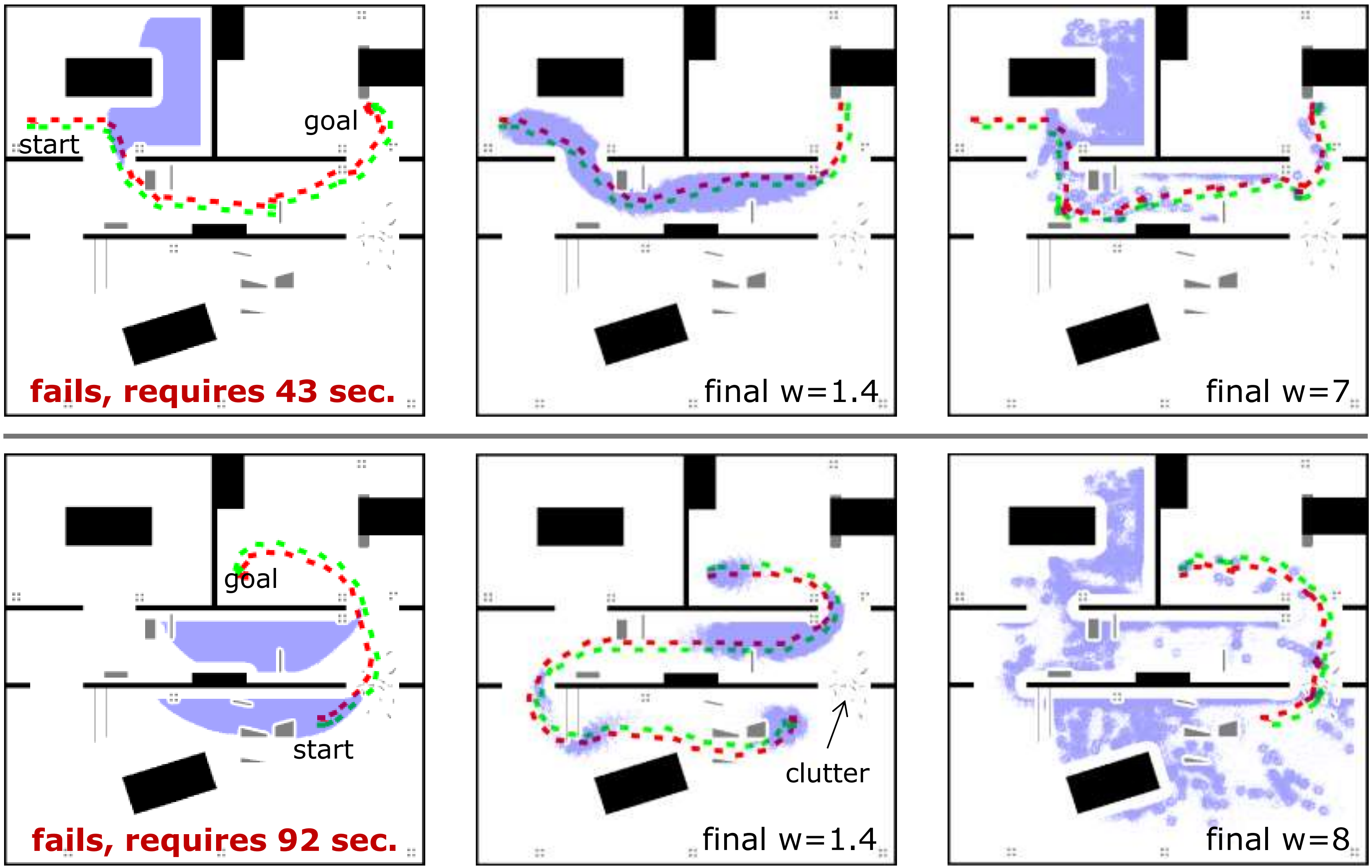
- 12 random start and goal locations
- ARA* finds fast results only with the 2D Dijkstra heuristic, leading to longer paths due to its inadmissibility
- **R* finds fast results even with the Euclidean heuristic**

Planning with Time Limit 5s

ARA*
Euclidean heuristic

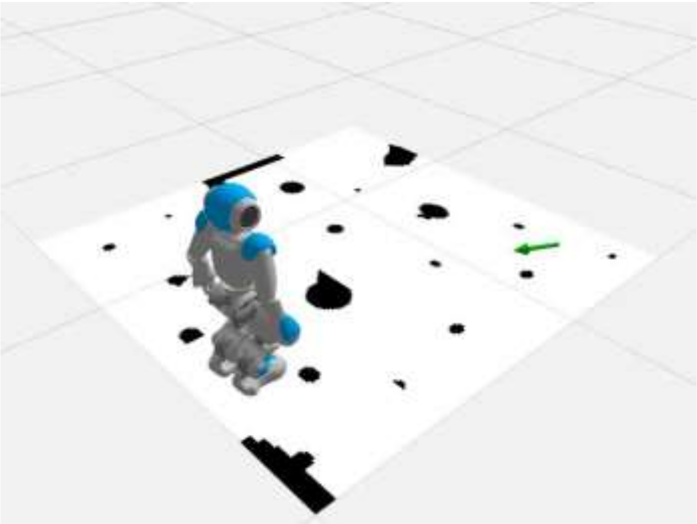
ARA*
Dijkstra heuristic

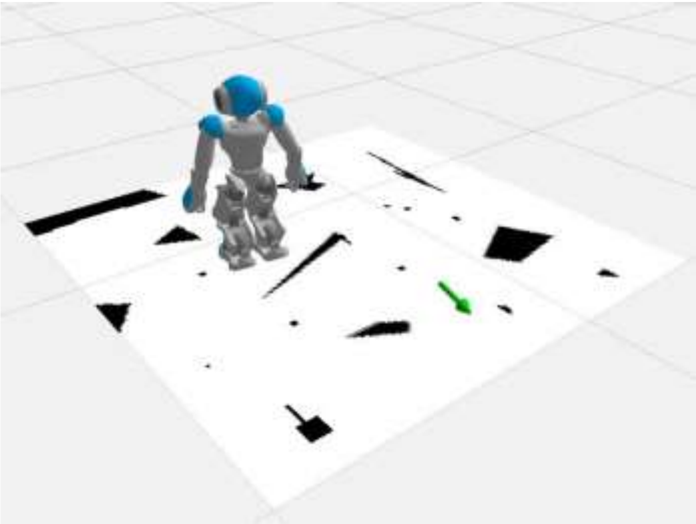
R*
Euclidean heuristic



Anytime Planning Results

- Performance of ARA* depends on well-designed heuristic
- Dijkstra heuristic may be inadmissible and can lead to wrong results
- R* with the Euclidean heuristic finds efficient plans in short time



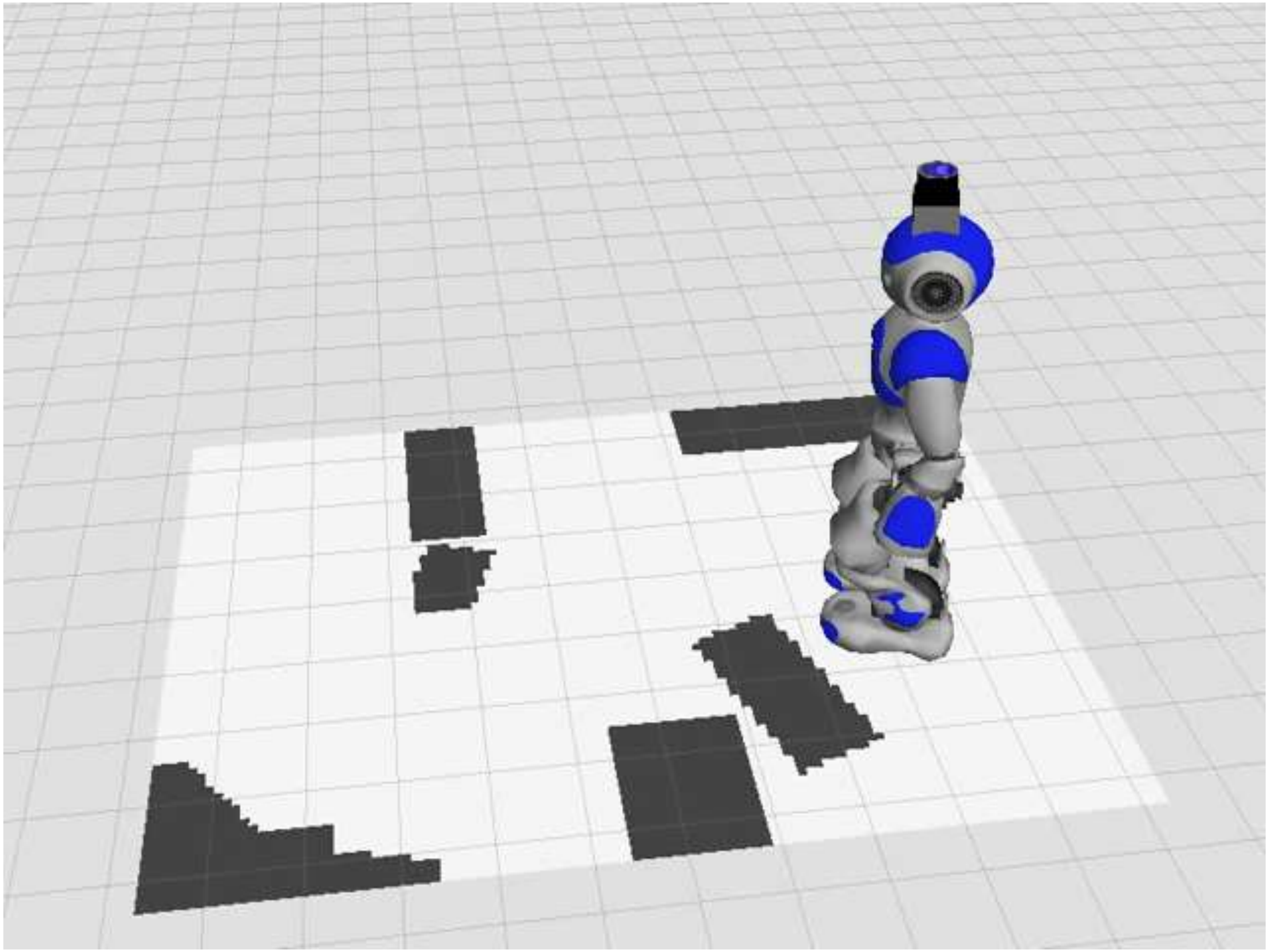


Dynamic A* (D*)

- Allows for efficient re-planning in case of
  - Changes in the environment
  - Deviations from the initial path
- Re-uses state information from previous searches
- Planning backwards increases the efficiency in case of updated localization estimates
- Anytime version: AD*

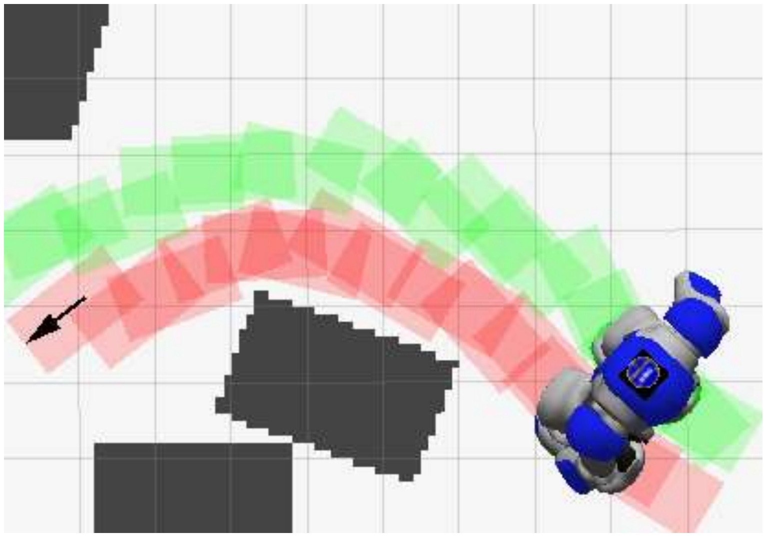
[Koenig & Likhachev (AAAI ‘00), Garimort (ICRA ’11)]

D* Plan Execution with a Nao

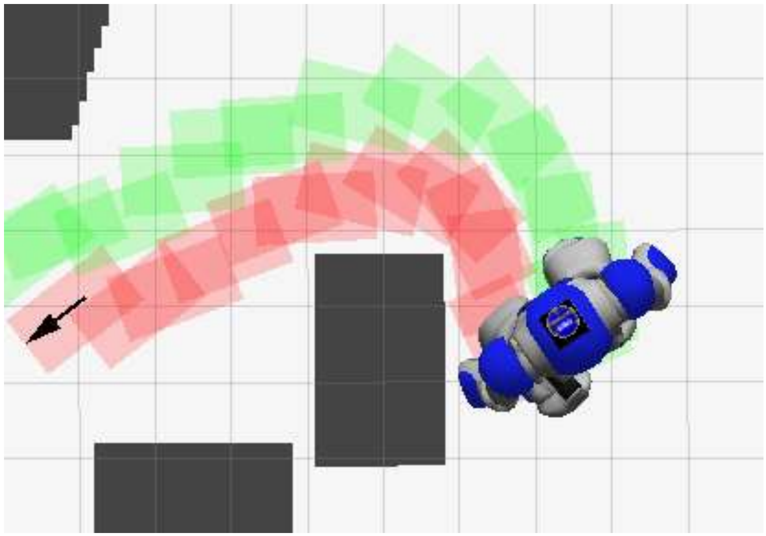


Efficient Replanning

- Plans may become invalid due to changes in the environment
- D* allows for efficient plan re-usage



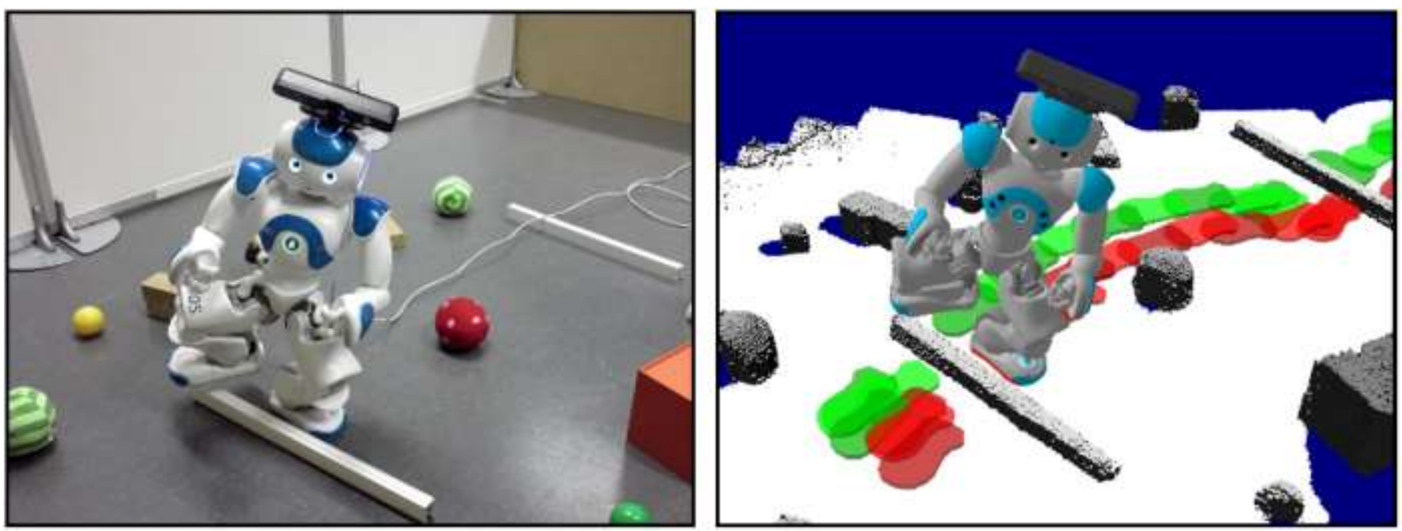
2966 states, 1.05s



956 states, 0.53s

Extension to 3D

- Depth camera for visual perception
- Scan matching to reduce drift of odometry
- Heightmap as environment representation
- Footstep planning and collision-checking on heightmap



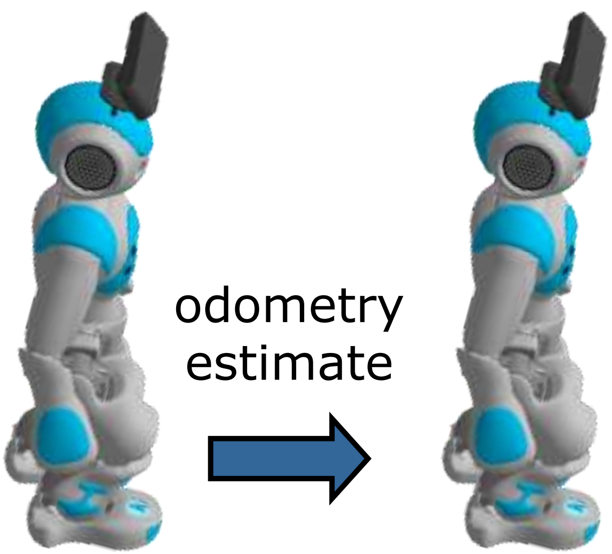
Maier et al. (to appear IROS 2013)]

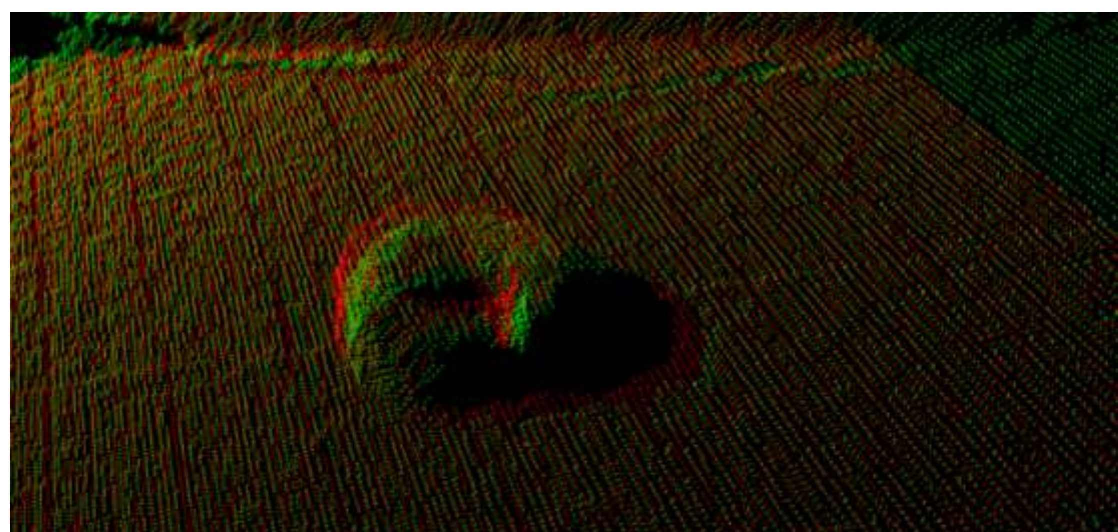
Depth Cameras for Robot Navigation

- Dense depth information
- Lightweight
- Cheap

Pose Estimation

- Odometry estimate is error-prone due to slippage of the feet and noisy sensors
- Accordingly, consecutive depth camera observations may not align
- Error accumulates over time
- Scan matching to reduce the error





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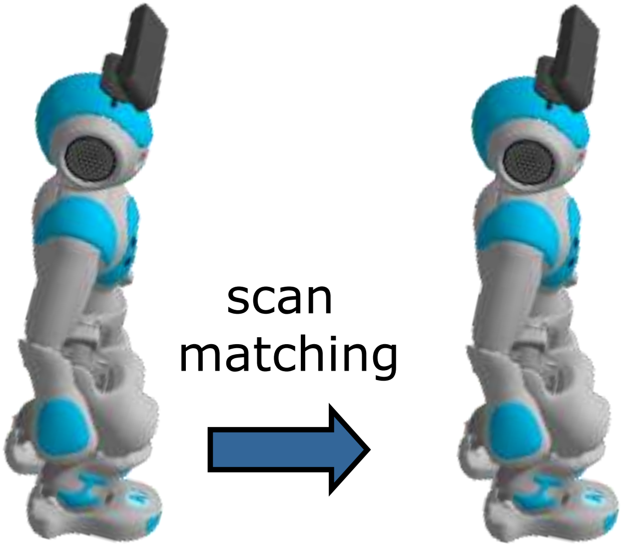
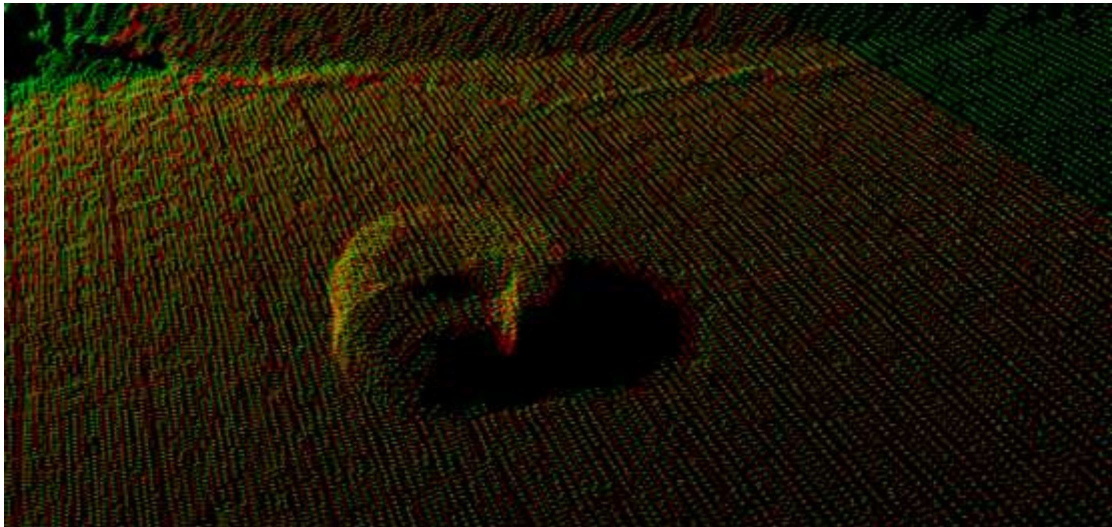
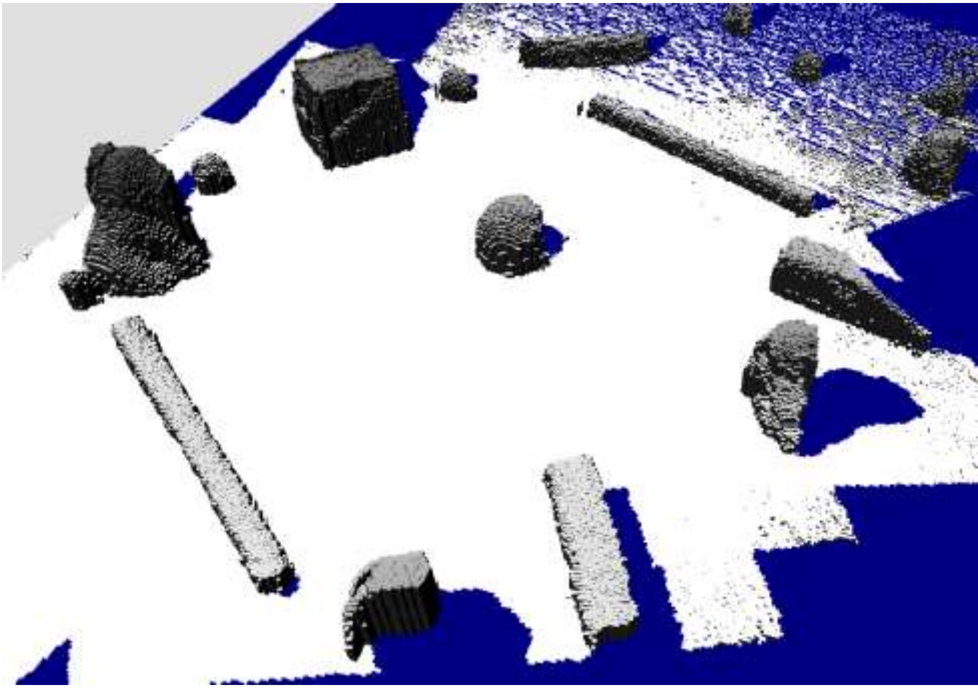


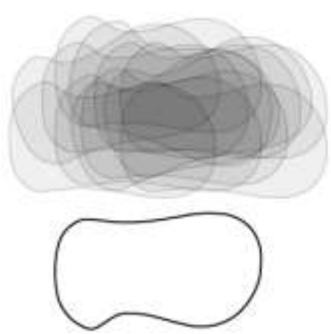


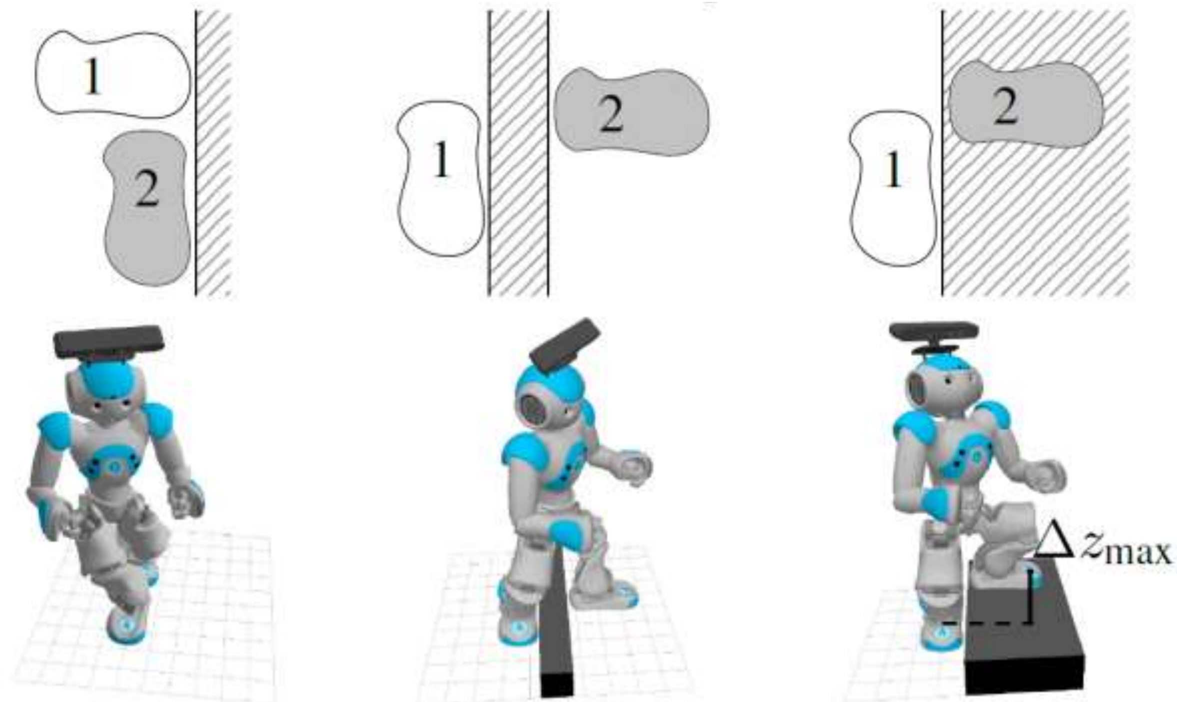
Heightmap Learned from Depth-Camera Observations

- 2D gridmap
- Probabilistic height estimate for each cell
- Conservative updates
- Quick access
- Memory efficient
- High resolution



Action Set for a Nao Humanoid





T-Step step over step onto

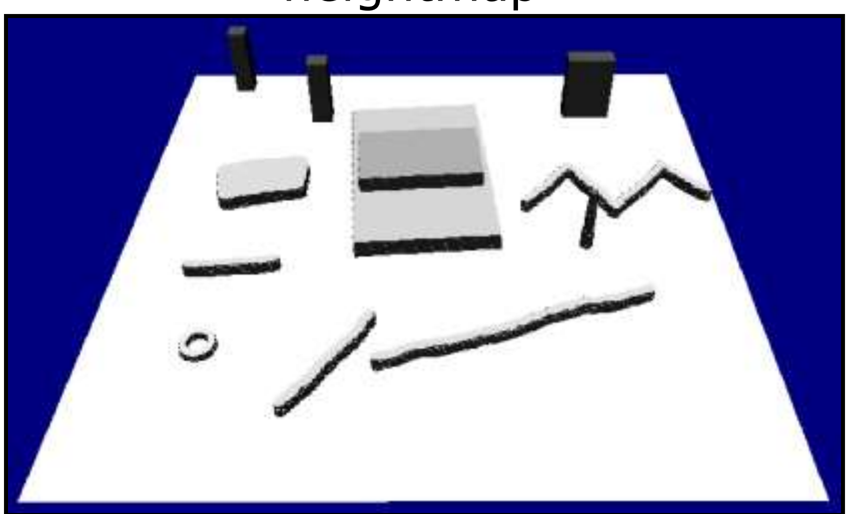
Standard planar steps

Extended 3D stepping capabilities

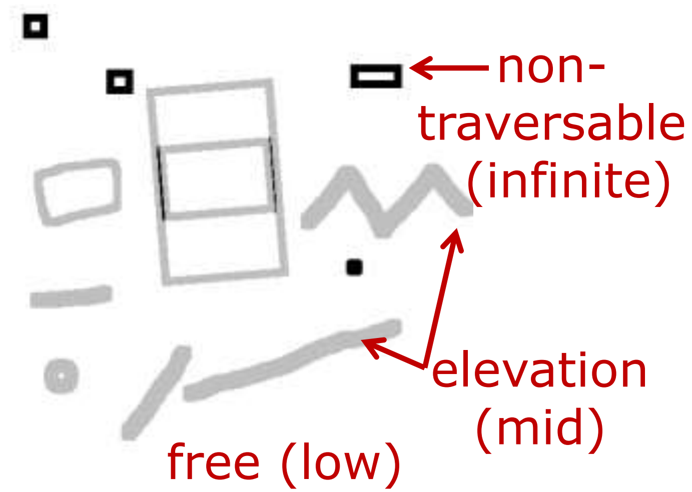
Dijkstra Heuristic for Heightmaps

- Graph G=(V,E)
  - V: discrete locations in the (x,y)-space
  - E: union of 8-neighborhoods in the state space
- Costs of an edge are defined by the height differences in the heightmap
- h(s): shortest path in G to the goal / $v_{\max}$

heightmap

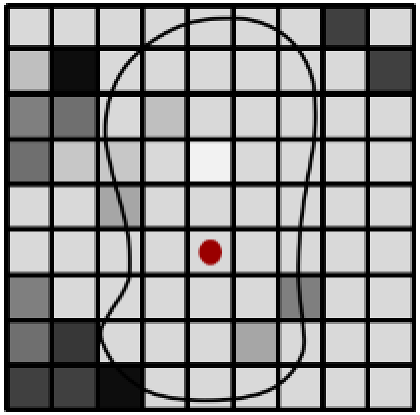


example costs

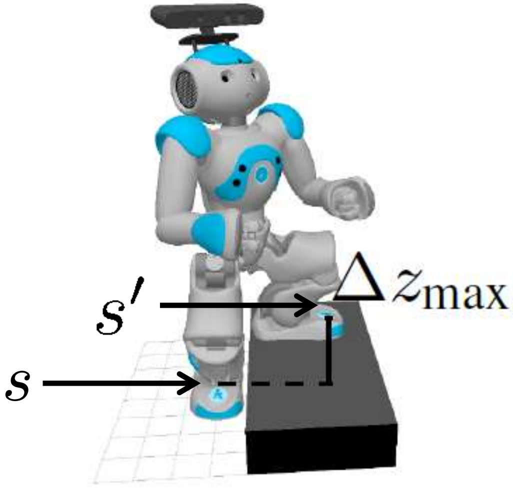


Safe Stepping Actions

- Allow only states where all cells covered by the footprint have a small height difference



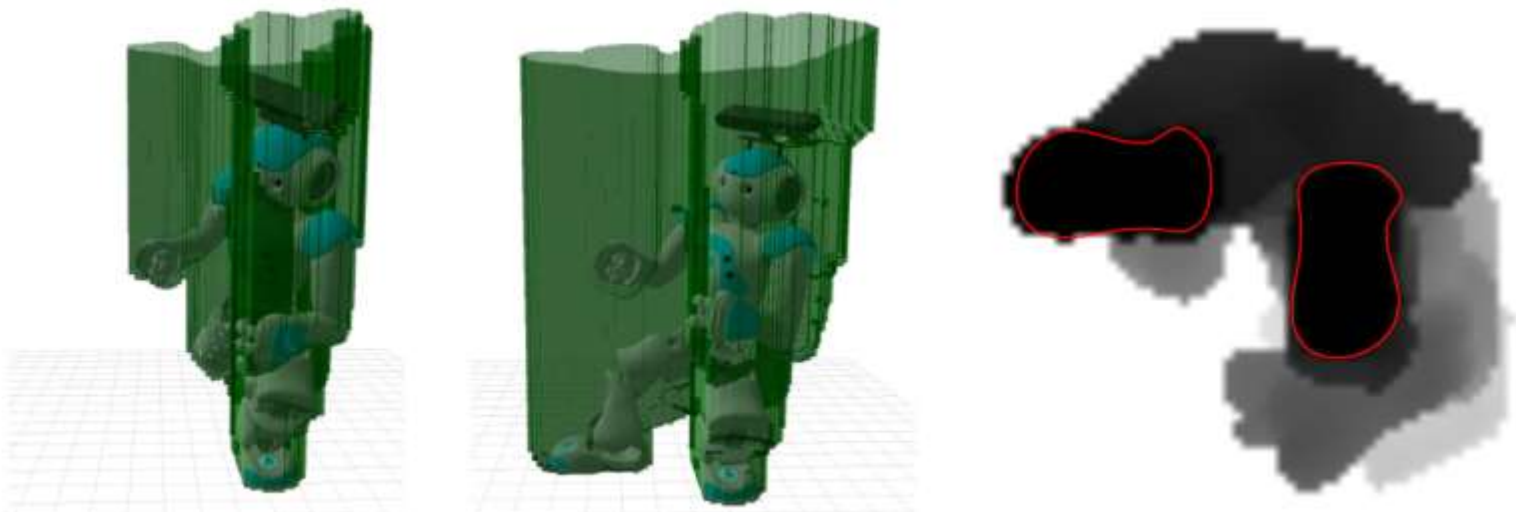
- Height difference between s and $s' = a(s)$ must be within the limits $[\Delta z_{\mathrm{min}}, \Delta z_{\mathrm{max}}]^a$ allowed by the action a



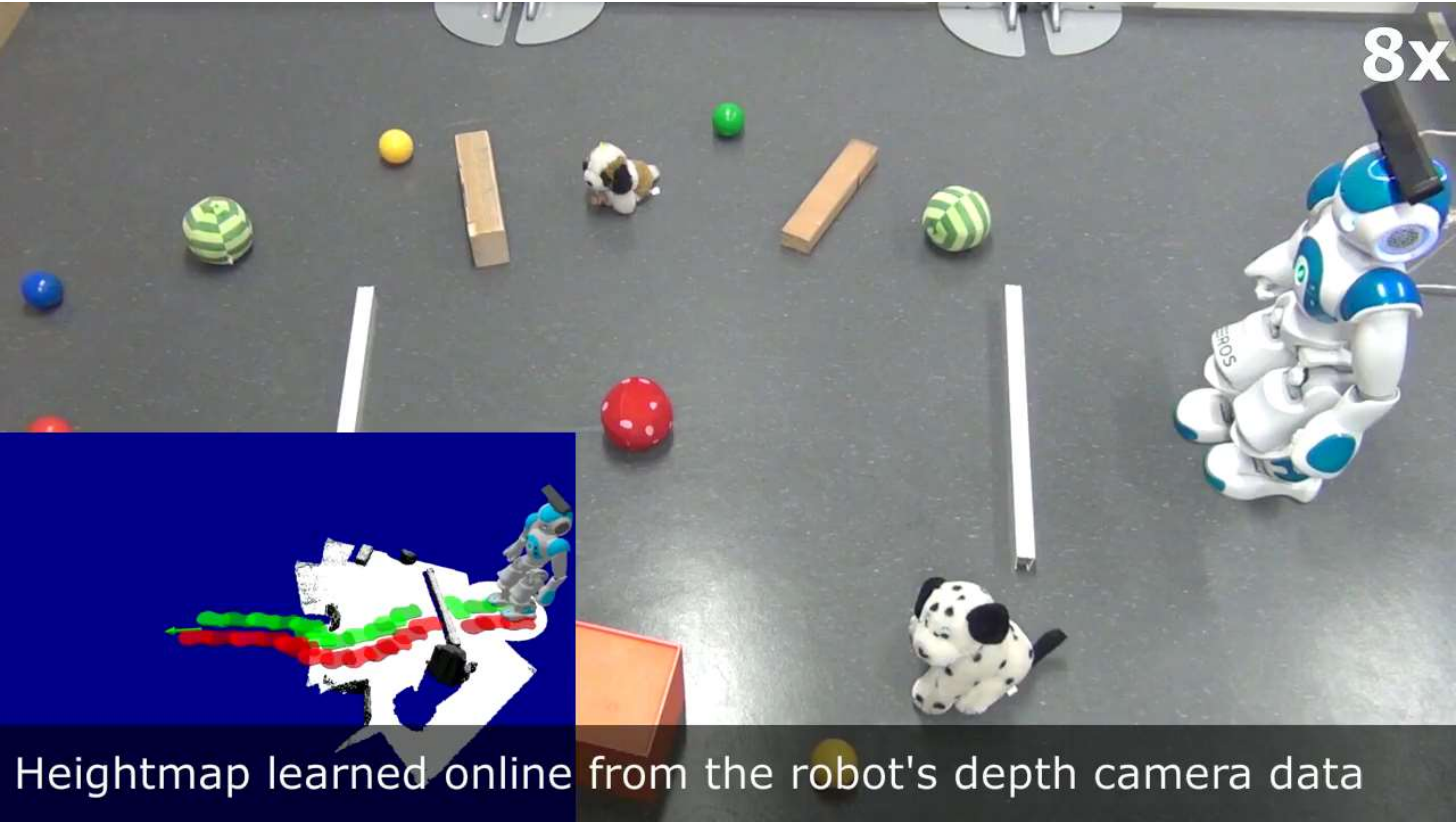
Whole-Body Collision Checking

- Project swept volume of a motion to the ground plane: inverse heightmap (IHM)
- An action a at state s is safe if

$$\forall (u,v) \in \mathrm{IHM}^a : \mathrm{IHM}^a_{(u,v)} + z_s > h_{(u,v)}$$

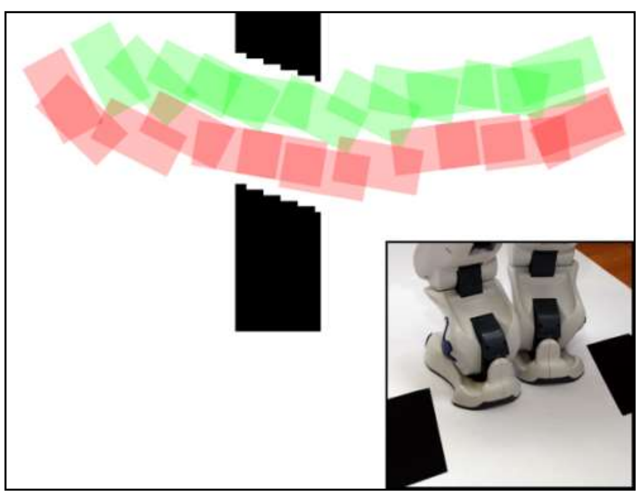


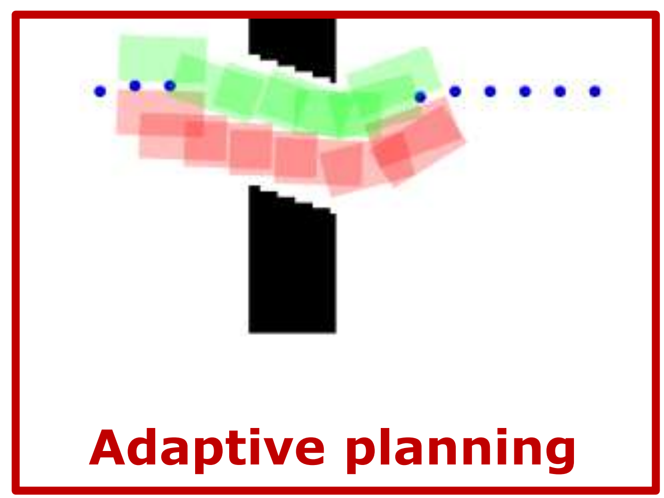
Navigation Experiments



Adaptive Level-of-Detail Planning

- Planning the whole path with footsteps may not always be desired in large open spaces
- Adaptive level-of-detail planning: Combine fast grid-based 2D planning in open spaces with footstep planning near obstacles





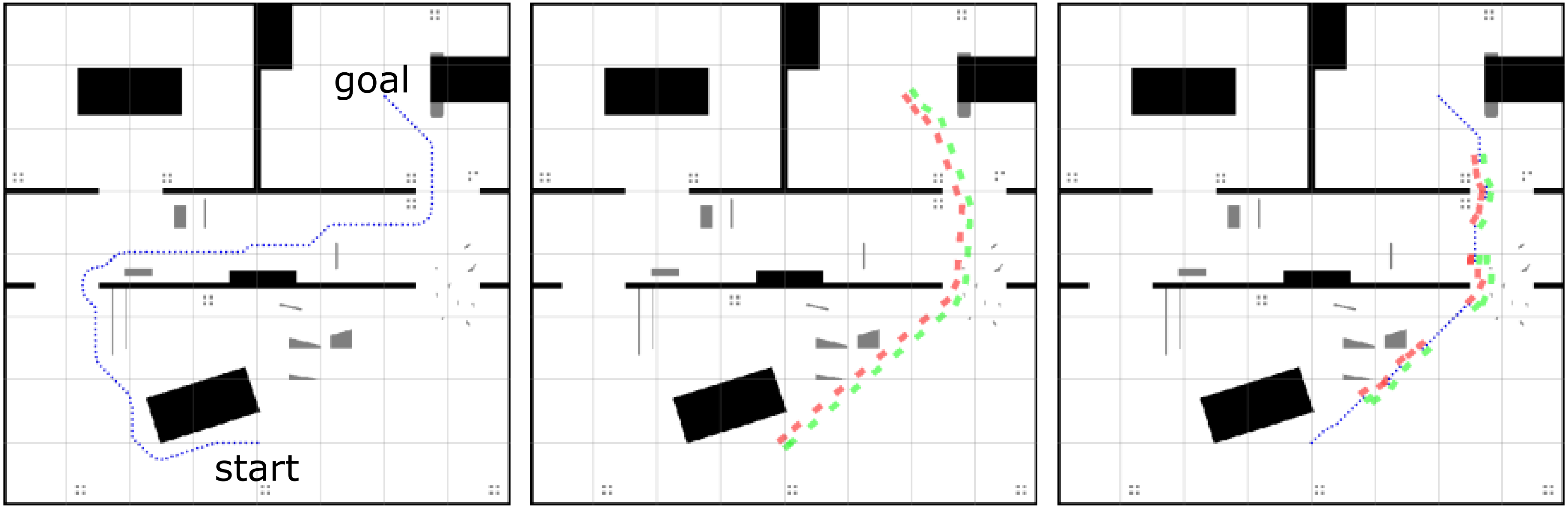
[Hornung & Bennewitz (ICRA ‘11)]

Adaptive Level-of-Detail Planning

- Allow transitions between neighboring cells in free areas and between sampled contour points across obstacle regions
- Traversal costs are estimated from a pre-planning stage or with a learned heuristic
- Every obstacle traversal triggers a footstep plan

Adaptive Planning Results

2D Planning | **Footstep Planning** | **Adaptive Planning**



<1 s planning time
High path costs

29 s planning time

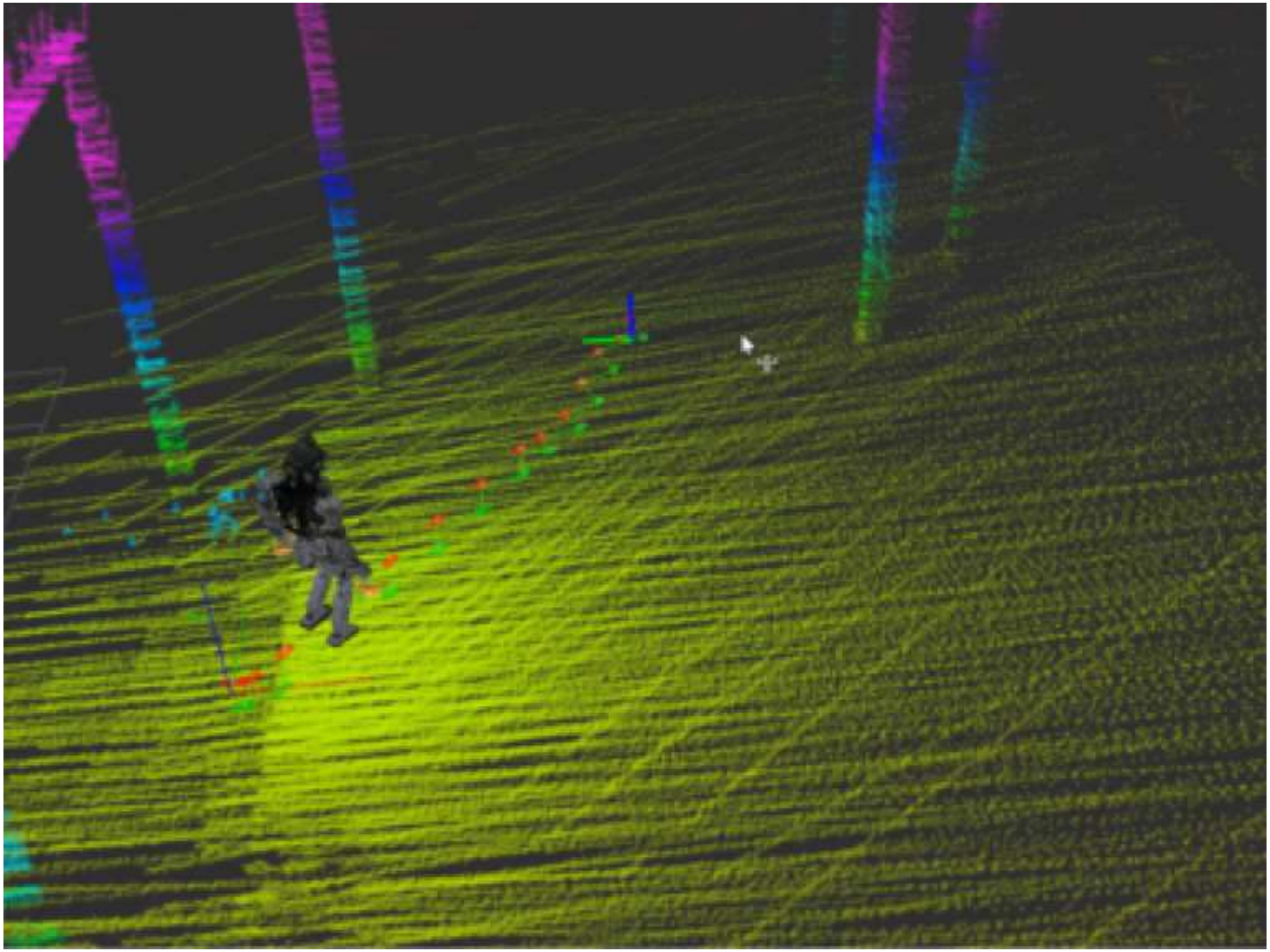
<1s planning time, costs only 2% higher

Fast planning times and efficient solutions with adaptive level-of-detail planning

Summary

- Anytime search-based footstep planning with suboptimality bounds: ARA* and R*
- Replanning during navigation with AD*
- Heuristic influences planner behavior
- Adaptive level-of-detail planning to combine 2D with footstep planning
- Extensions to 3D obstacles
- Available open source in ROS: www.ros.org/wiki/footstep_planner

Example: ATLAS humanoid in DRC (Team ViGIR)



Thank you!

Live Demo

- Install prerequisites:
  `sudo apt-get install ros-groovy-desktop-full python-rosdep python-rosinstall ros-groovy-sbpl`
- Follow rosinstall instructions at http://ros.org/wiki/humanoid_navigation (but don‘t compile)
- Compile with `rosmake footstep_planner`
- Start with `roslaunch footstep_planner footstep_planner_complete.launch`