Probabilistic Roadmaps for Path Planning in High-Dimensional Configuration Spaces

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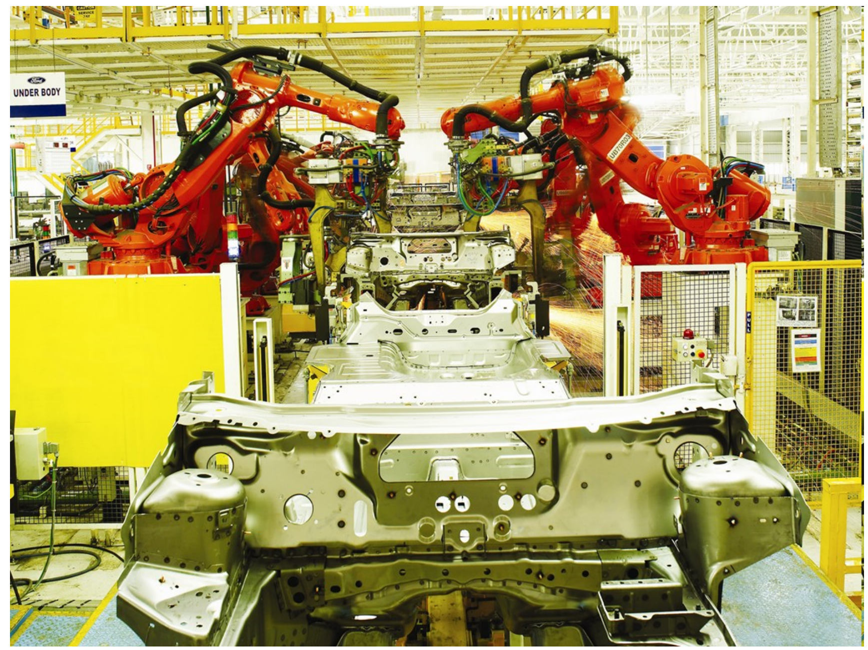
Agenda

- Motivation
- Introduction
- Previous Work
- The Method
- Experiments
- Results
- References

Motivation

- Applications:
  - Car assembly lines
  - Nuclear plant cooling pipes
  - Cleaning airplane fuselages

- Complex workspaces
- Tedious programming
- Efficient, reliable planner required to reduce burden



Introduction

- Motion planning in static workspaces
- Holonomic robots, with many degrees of freedom
- Static obstacles, avoid collision
- Problem definition:

"Compute a collision-free path for a holonomic object (virtually any type of robot, with many degrees of freedom) among static obstacles"

Introduction (contd.)

- Inputs:
  - Geometry of robot and obstacles
  - Kinematics of robot (degrees of freedom)
  - Initial and goal robot configurations (placements)
- Outputs:
  - Continuous sequence of collision-free robot configurations connecting the initial and goal configurations
- Robotic Arm Video

Source: http://ai.stanford.edu/~latombe/projects/motion-planning.ppt

Previous Work

- Potential Fields: http://www.youtube.com/watch?v=r9FD7P76zJs
- Potential field / cell decomposition based methods
  - RPP (fails for several examples, falling into local minima bounded by obstacles)
  - variational dynamic programming
  - Use of genetic algorithms
- Roadmap based methods
  - Visibility graph (low dimension C-spaces)
  - Voronoi diagram (low dimension C-spaces)
  - Silhouette method (any dimension but complex, hence impractical)

The Method

- Learning Phase
  - Construction: reasonably connected graph covering C-space
  - Expansion: improve connectivity
  - Local paths not memorized (cheap to re-compute)

The Method (contd.)

Construction step algorithm:

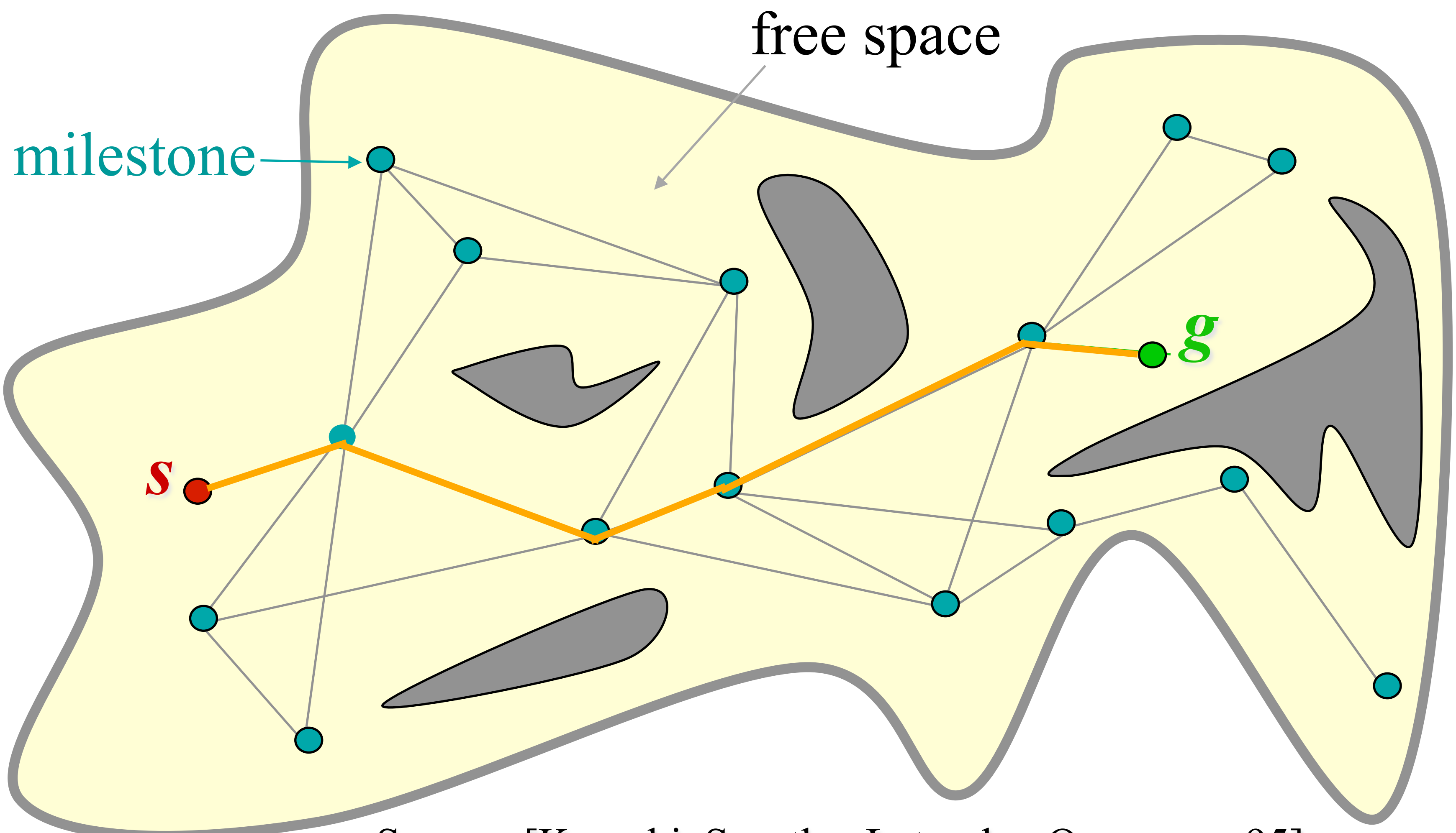
$N \leftarrow \emptyset$
$E \leftarrow \emptyset$
loop
  $c \leftarrow$ a randomly chosen free configuration
  $N_c \leftarrow$ a set of candidate neighbors of c chosen from N
  $N \leftarrow N \cup \{c\}$
  for all $n \in N_c$, in order of increasing $D(c, n)$ **do**
    if $\neg$*same_connected_component*(c, n) $\wedge \Delta(c, n)$ **then**
      $E \leftarrow E \cup \{(c, n)\}$
      update R's connected components

Source: Probabilistic roadmaps for path planning in high-dimensional configuration spaces.pdf

The Method (contd.)

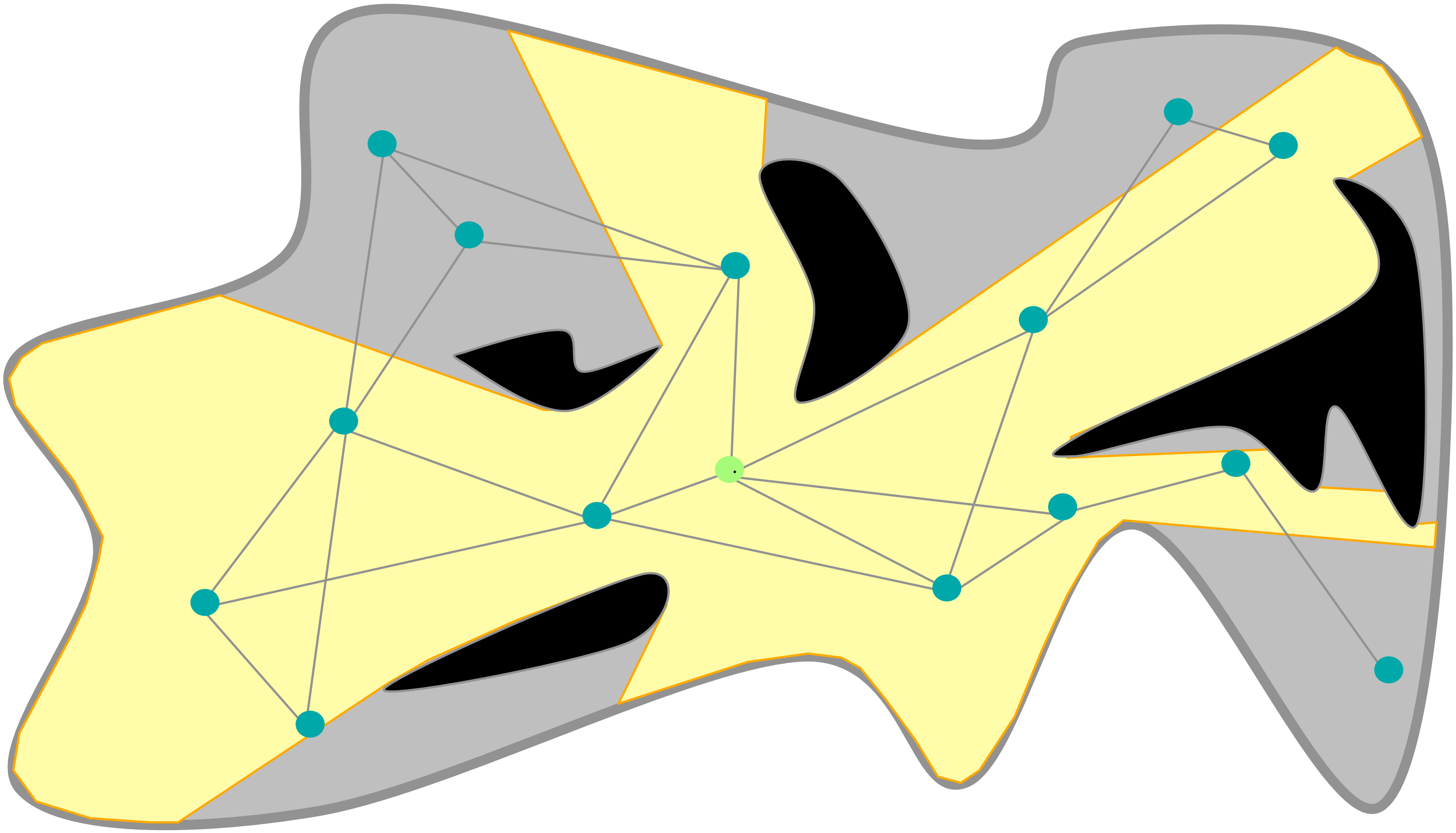
- Query Phase
  - Connect start and goal configurations to roadmap (say, ŝ and ĝ)
  - Find path between ŝ and ĝ in roadmap
  - ŝ and ĝ should be in same connected component, else failure
  - If too many failures, increase learning time

Principle of Probabilistic Roadmaps



Source: [Kavraki, Svestka, Latombe, Overmars, 95] (http://ai.stanford.edu/~latombe/projects/motion-planning.ppt)

Probabilistic Roadmaps (contd.)



Source: [Kavraki, Latombe, Motwani, Raghavan, 95] (
http://ai.stanford.edu/~latombe/projects/motion-planning.ppt)

Properties of PRM Planners

- Is probabilistically complete, i.e., whenever a solution exists, the probability that it finds one tends toward 1 as the number N of milestones increases

- Under rather general hypotheses, the rate of convergence is exponential in the number N of milestones, i.e.:

$$\text{Prob[failure]} \sim \exp(-N)$$

Source: http://ai.stanford.edu/~latombe/projects/motion-planning.ppt

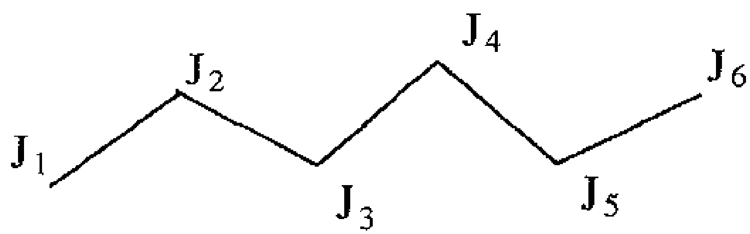
Properties of PRM Planners (contd.)

- Are fast
- Deal effectively with many – dof robots
- Are easy to implement
- Have solved complex problems

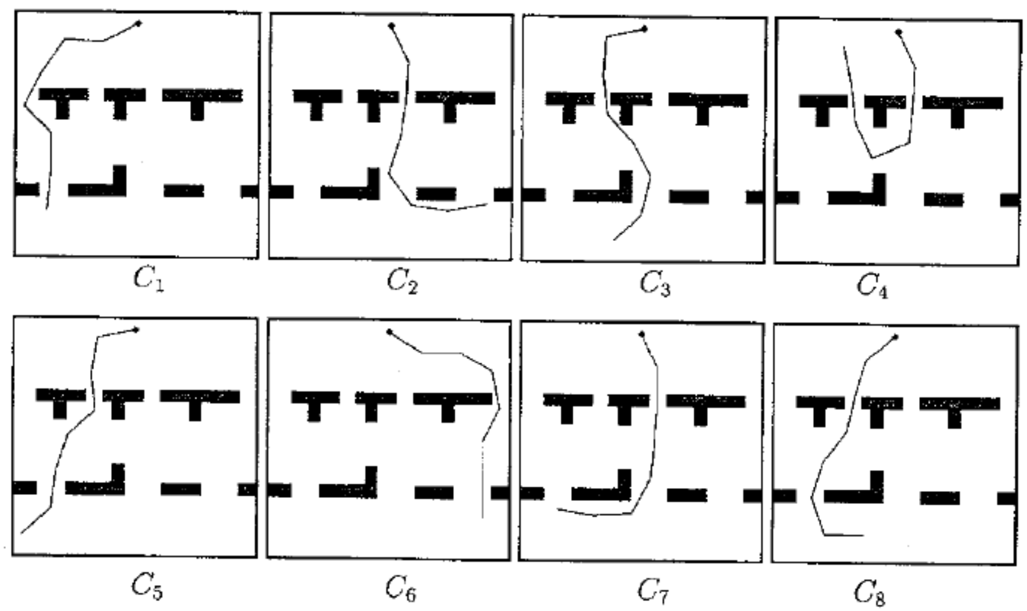
Experiments

- Customized planner used
- Parameters adjusted
  - T_C , time for construction step
  - T_E , time for expansion step
  - maxdist, distance between nodes
  - eps, constant for discretization of local paths
  - maxneighbours, no. of calls to local planner
  - $T_{RB\text{-}EXPAND}$, duration for each random bounce walk
  - $N_{RB\text{-}QUERY}$, max no. of random bounce walks
  - $T_{RB\text{-}QUERY}$, duration for each random bounce walk

Experiments (contd.)



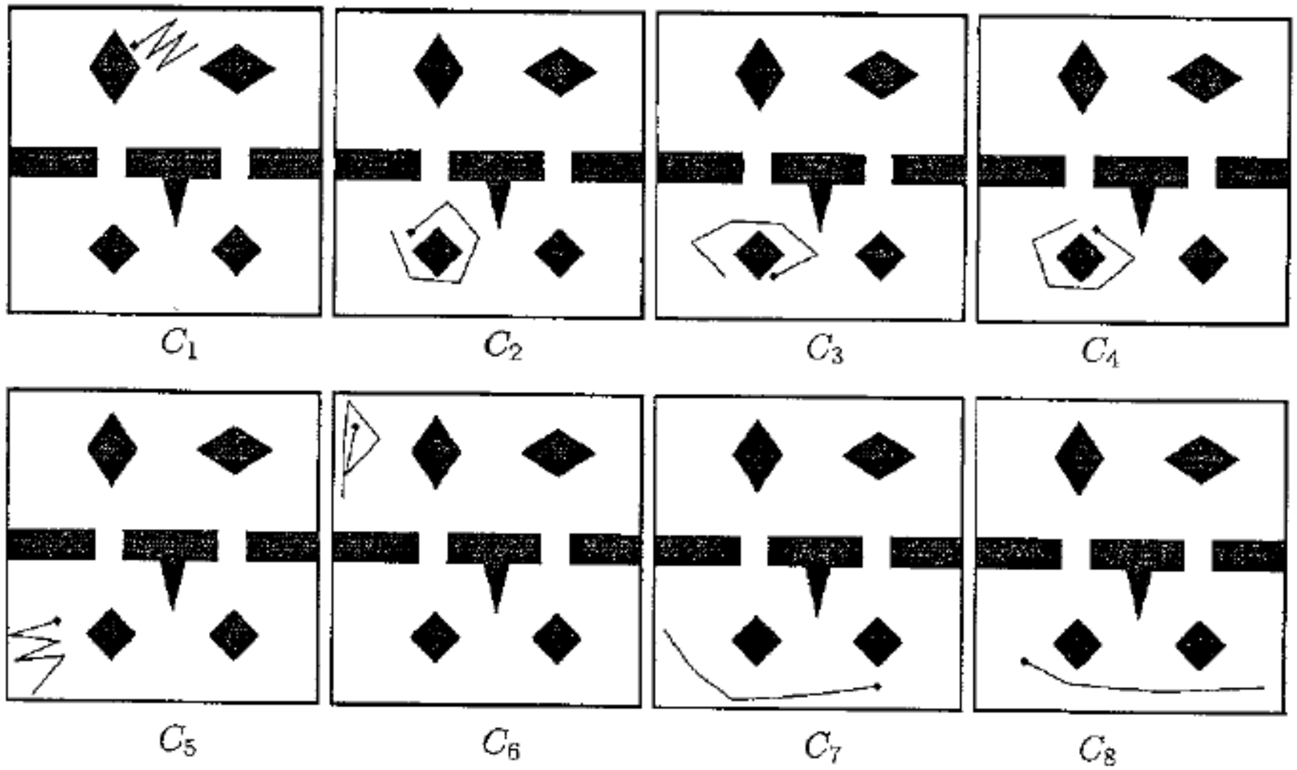
Experimental Planar Articulated Robot



Experimental Setup 1: For 7-revolute-joint fixed base robot

Source: Probabilistic roadmaps for path planning in high-dimensional configuration spaces.pdf

Experiments (contd.)



Experimental Setup 2: For 5-revolute-joint free base robot (7 dof)

Source: Probabilistic roadmaps for path planning in high-dimensional configuration spaces.pdf

Results

T_L (sec)	T_C (sec)	T_E (sec)	Coll. checks	Avg. nodes	Success Rate (%)							
					C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
20.1	13.1	7.0	621943	1062	100.0	36.7	56.7	36.7	53.3	100.0	36.7	60.0
30.1	19.5	10.6	889384	1643	100.0	66.7	70.0	66.7	76.7	100.0	66.7	80.0
40.3	26.3	14.0	1145091	2233	100.0	90.0	86.7	90.0	86.7	100.0	90.0	86.7
50.3	32.7	17.6	1392454	2783	100.0	96.7	96.7	96.7	96.7	100.0	96.7	96.7
60.2	39.1	21.1	1631612	3284	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
70.3	45.8	24.5	1876006	3805	100.0	96.7	100.0	96.7	100.0	100.0	96.7	100.0
80.4	52.2	28.2	2104209	4272	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

For experimental setup 1 (with expansion)

T_L (sec)	T_C (sec)	T_E (sec)	Coll. checks	Avg. nodes	Success Rate (%)							
					C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
20.0	20.0	0.0	597559	1011	100.0	13.3	36.7	10.0	40.0	93.3	13.3	36.7
30.1	30.1	0.0	852038	1601	100.0	50.0	46.7	46.7	46.7	90.0	53.3	46.7
40.2	40.2	0.0	1086053	2300	100.0	80.0	80.0	80.0	80.0	100.0	80.0	80.0
50.2	50.2	0.0	1291216	2877	100.0	90.0	96.7	90.0	96.7	100.0	90.0	96.7
60.2	60.2	0.0	1502089	3372	100.0	90.0	100.0	90.0	100.0	100.0	90.0	100.0
70.2	70.2	0.0	1688544	3877	100.0	96.7	100.0	96.7	100.0	100.0	96.7	100.0
80.3	80.3	0.0	1860341	4295	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

For experimental setup 1 (without expansion)

Source: Probabilistic roadmaps for path planning in high-dimensional configuration spaces.pdf

Results (contd.)

T_L (sec)	T_C (sec)	T_E (sec)	Coll. checks	Avg. nodes	Success Rate (%)							
					C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
20.1	13.0	7.1	712661	541	96.7	6.7	6.7	6.7	6.7	86.7	6.7	10.0
30.1	19.6	10.5	1037739	924	100.0	16.7	16.7	16.7	16.7	90.0	16.7	16.7
40.1	26.0	14.1	1361134	1603	100.0	60.0	63.3	56.7	56.7	96.7	56.7	56.7
50.2	32.6	17.6	1674144	2460	100.0	93.3	93.3	93.3	93.3	100.0	96.7	93.3
60.3	39.2	21.1	1987967	2999	100.0	93.3	93.3	93.3	93.3	100.0	93.3	93.3
70.1	45.6	24.5	2336917	3695	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
80.4	52.3	28.1	2632712	4229	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

For experimental setup 2 (with expansion)

T_L (sec)	T_C (sec)	T_E (sec)	Coll. checks	Avg. nodes	Success Rate (%)							
					C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
20.0	20.0	0.0	686580	527	96.7	3.3	3.3	3.3	3.3	86.7	3.3	3.3
30.0	30.0	0.0	987852	1005	100.0	30.0	30.0	26.7	30.0	96.7	30.0	30.0
40.3	40.3	0.0	1265245	1437	100.0	40.0	40.0	40.0	43.3	100.0	43.3	40.0
50.1	50.1	0.0	1534808	2238	100.0	80.0	80.0	76.7	76.7	100.0	76.7	76.7
60.0	60.0	0.0	1778678	2709	100.0	80.0	80.0	80.0	80.0	100.0	83.3	80.0
70.0	70.0	0.0	2058469	3384	100.0	90.0	90.0	90.0	90.0	100.0	90.0	90.0
80.2	80.2	0.0	2277226	4002	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

For experimental setup 2 (without expansion)

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References

- http://ai.stanford.edu/~latombe/projects/motion-planning.ppt
- http://ai.stanford.edu/~latombe/projects/grenoble2000.ppt
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- http://ai.stanford.edu/~mitul/mpk/index.html