Improving Path Planning Methods Using Machine Learning

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12.06.2024

Introduction

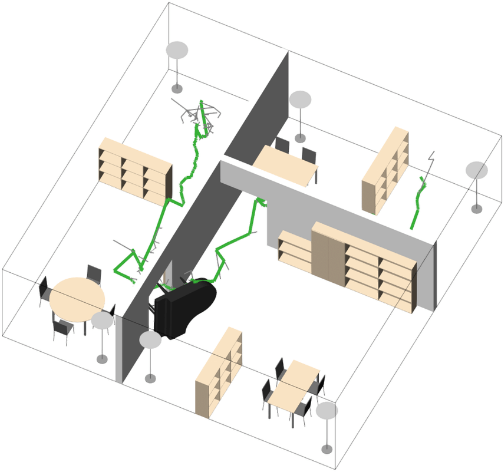


Figure: The Piano Movers Problem. Image courtesy of [1].

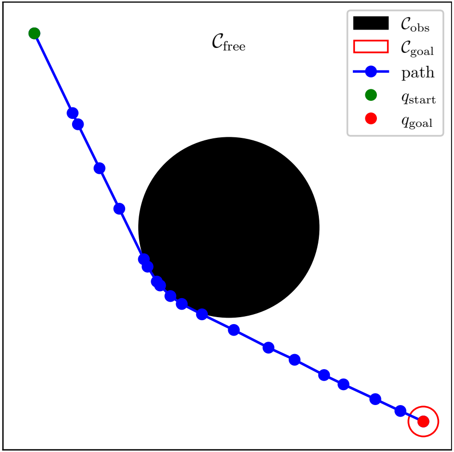
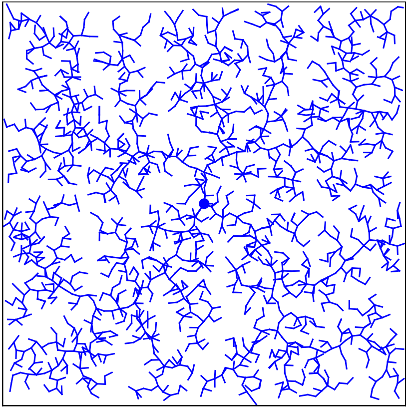
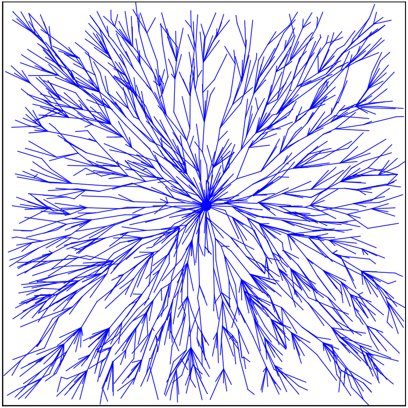


Figure: 2D workspace with a 2D $\mathcal{C}$-space.

RRT and RRT*



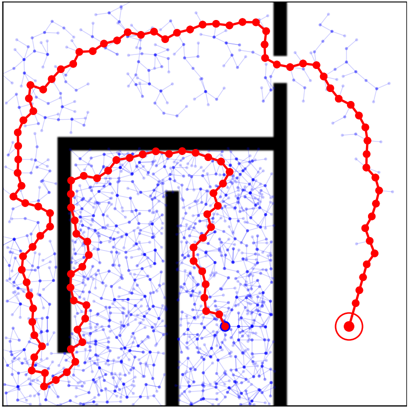
(a) RRT.



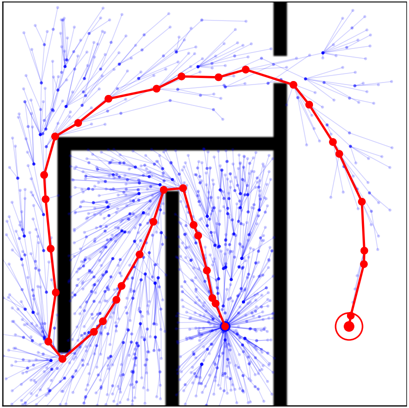
(b) RRT*.

Figure: RRT and RRT* comparison.

RRT and RRT*



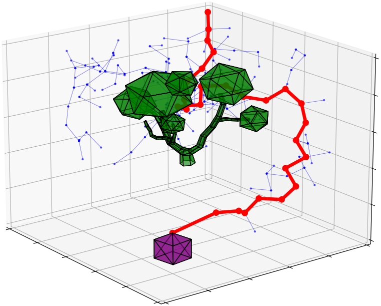
(a) RRT.



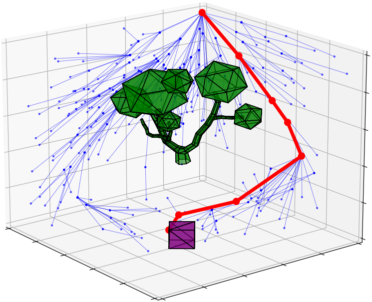
(b) RRT*.

Figure: RRT and RRT* comparison.

RRT and RRT*



(a) RRT.



(b) RRT*.

Figure: RRT and RRT* comparison.

Proposed solution

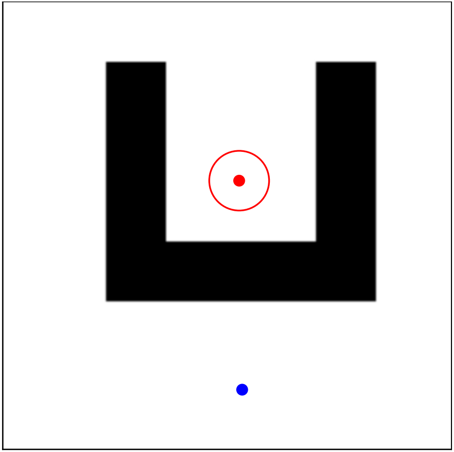


Figure: An example of the 2D workspace with a 2D $\mathcal{C}$-space.

Proposed solution

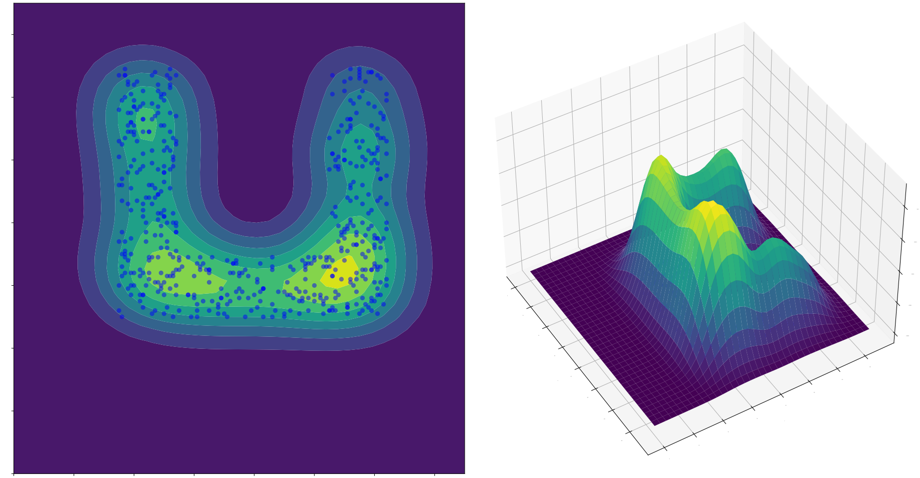


Figure: Obstacle density.

Proposed solution

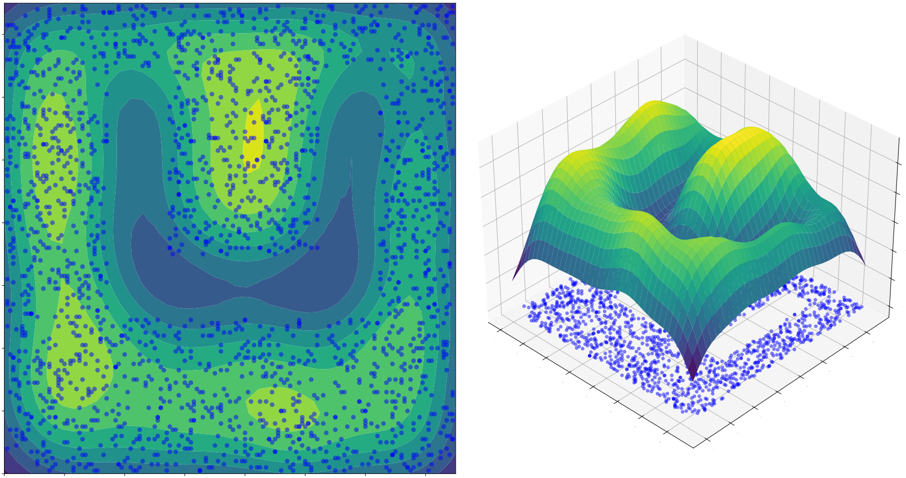


Figure: Obstacle-free density.

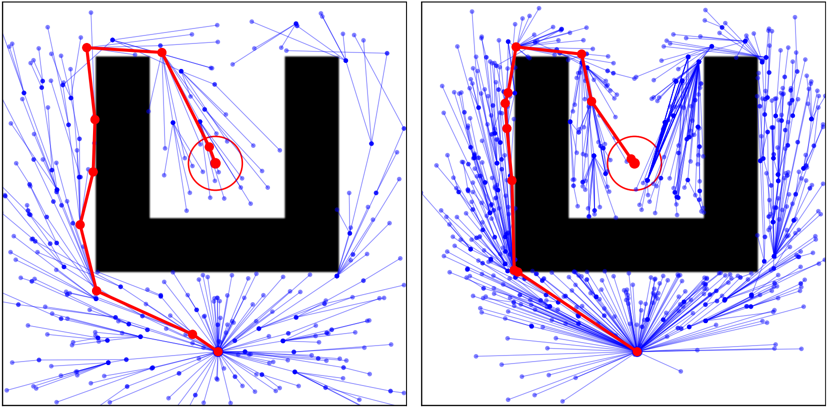
Proposed Solution

Algorithm 1: Sample Density

Data: $\mathcal{X}_{\text{obs}}$, $\mathcal{X}_{\text{free}}$
Result: Predicted sampled point x

$\gamma_{\text{free}} \leftarrow 0$;
$\gamma_{\text{obs}} \leftarrow 1$;
while $\gamma_{free} < \gamma_{obs}$ **do**
  $x_{\text{rand}} \leftarrow \text{RandomConfiguration}()$;
  $P_{\text{free}} \leftarrow \frac{|\mathcal{X}_{\text{free}}|}{|\mathcal{X}_{\text{free}}|+|\mathcal{X}_{\text{obs}}|}$;
  $P_{\text{obs}} \leftarrow 1 - P_{\text{free}}$;
  $b_{\text{free}} \leftarrow \text{DensityEstimator}(x_{\text{rand}}, \mathcal{X}_{\text{free}})$;
  $b_{\text{obs}} \leftarrow \text{DensityEstimator}(x_{\text{rand}}, \mathcal{X}_{\text{obs}})$;
  $\gamma_{\text{free}} \leftarrow b_{\text{free}} \cdot P_{\text{free}}$;
  $\gamma_{\text{obs}} \leftarrow b_{\text{obs}} \cdot P_{\text{obs}}$;
$x \leftarrow x_{\text{rand}}$;
return x;

Proposed solution



(a) RRT*. (b) Improved RRT*.

Figure: RRT* and Improved RRT* comparison.

Proposed solution

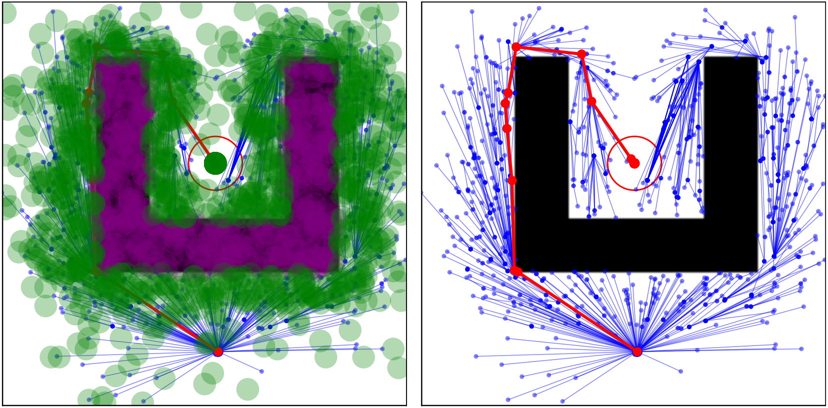


Figure: Learning the $\mathcal{C}$-space.

Proposed solution

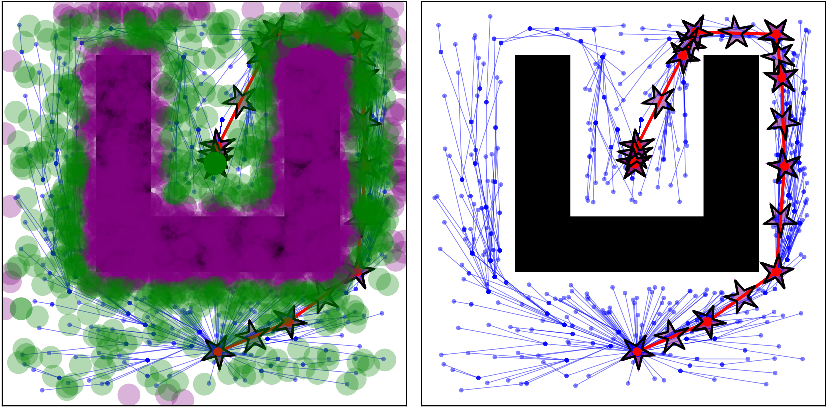
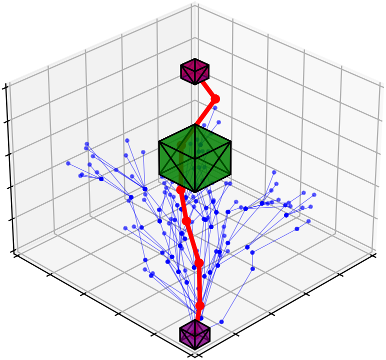
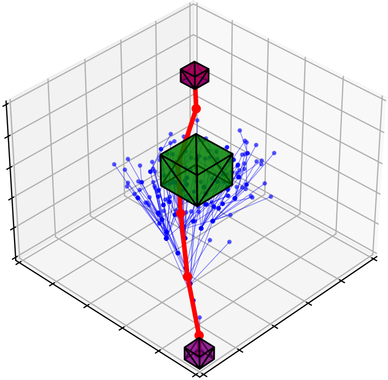


Figure: Learning the $\mathcal{C}$-space.

Proposed solution



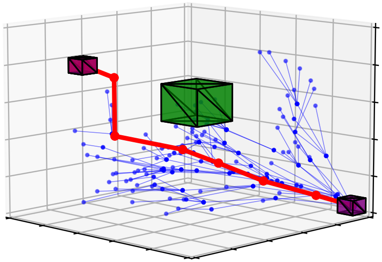
(a) RRT*.



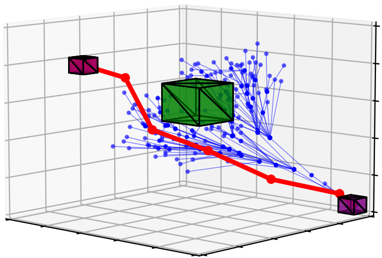
(b) Improved RRT*.

Figure: Front view.

Proposed solution



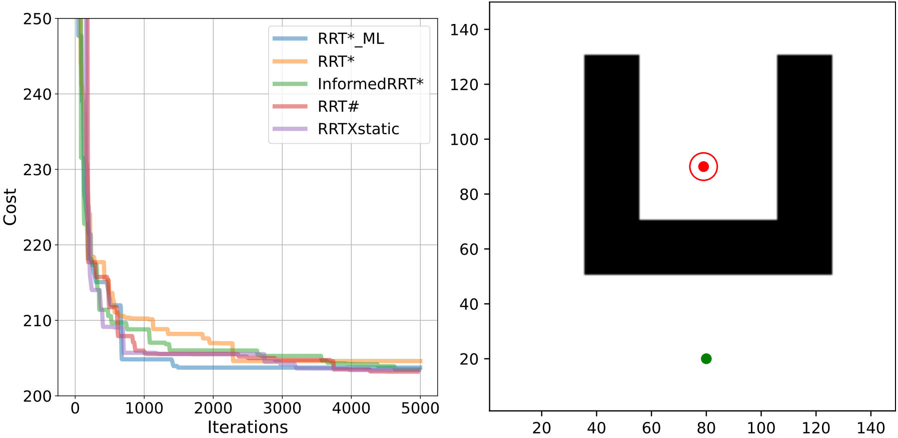
(a) RRT*.



(b) Improved RRT*.

Figure: Left view.

Results

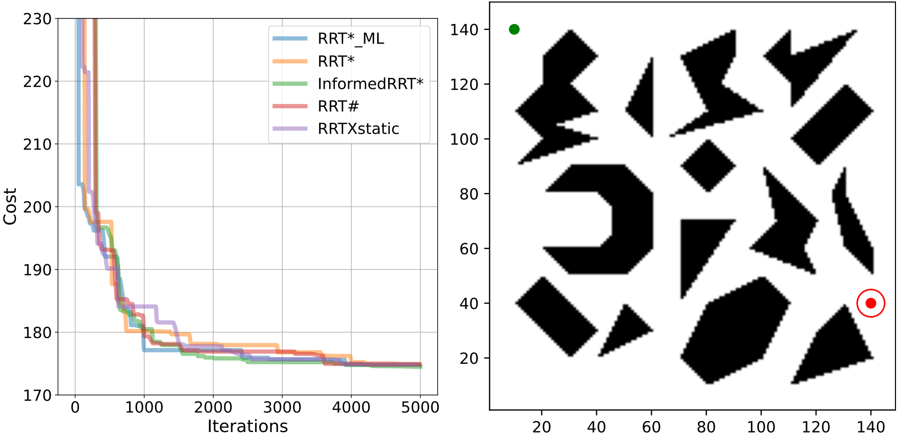


(a) Graph.

(b) Map.

Figure: Convergence graph for the corresponding map.

Results

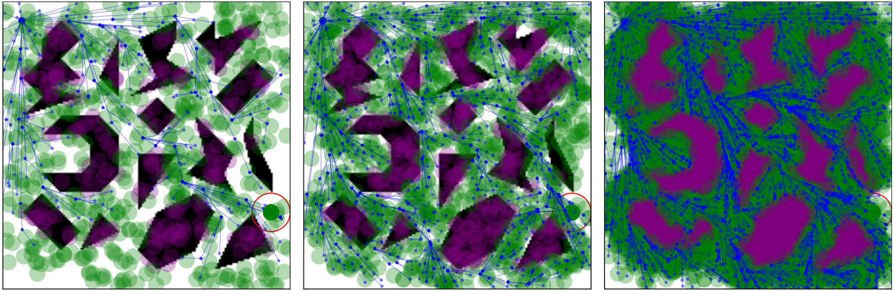


(a) Graph.

(b) Map.

Figure: Convergence graph for the cluttered map.

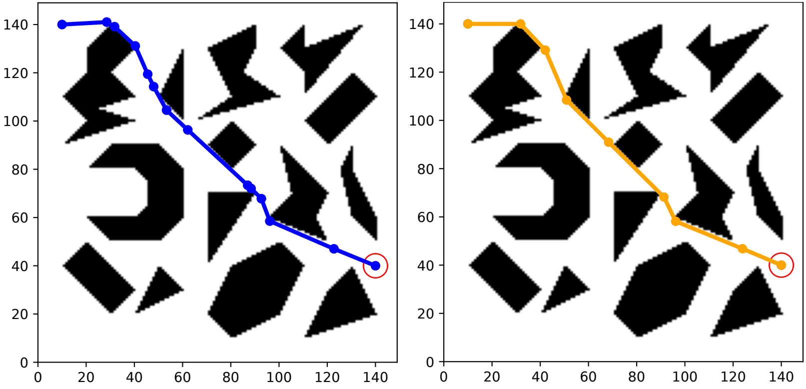
Results



(a) 500 iterations. (b) 1000 iterations. (c) 5000 iterations.

Figure: Learning $\mathcal{C}$-space in the cluttered map.

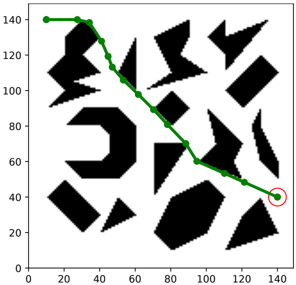
Results



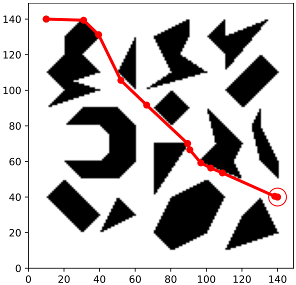
(a) RRT*_ML.   (b) RRT*.

Figure: Found solutions.

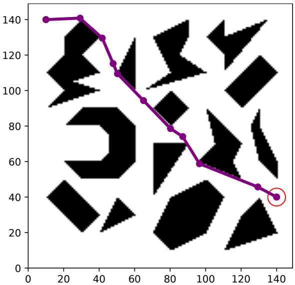
Results



(a) Informed RRT*.



(b) RRT$^{\#}$.



(c) RRT^X static.

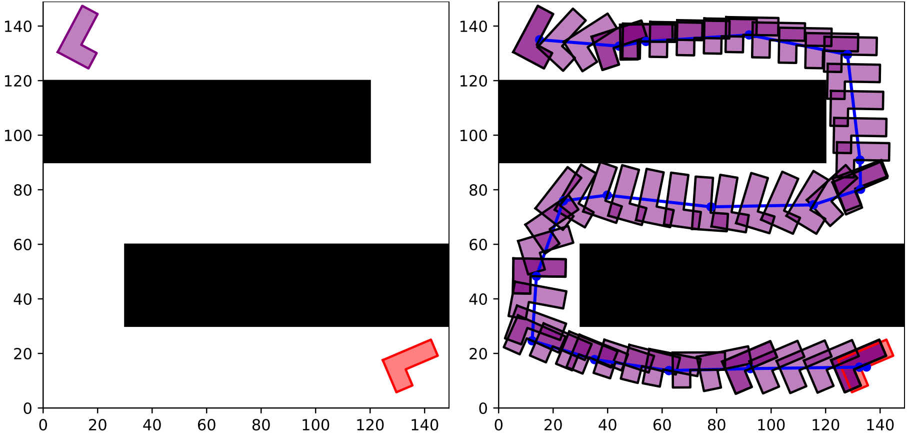
Figure: Found solutions.

Results

Runtime		
Planner	**Initial solution [s]**	**Final solution [s]**
RRT*_ML	0.278594 ± 0.157754	289.625891 ± 2.611068
RRT*	0.006518 ± 0.001462	0.321272 ± 0.014779
Informed RRT*	0.007330 ± 0.000536	0.259046 ± 0.003154
RRT$^{\#}$	0.011917 ± 0.002803	0.305096 ± 0.010232
RRT^{X} static	0.011775 ± 0.002566	0.305259 ± 0.008140

Table: Time spent to find the first and final solutions in the cluttered map.

Results



(a) Workspace and robot.

(b) Solution.

Figure: 3D $\mathcal{C}$-space.

Results

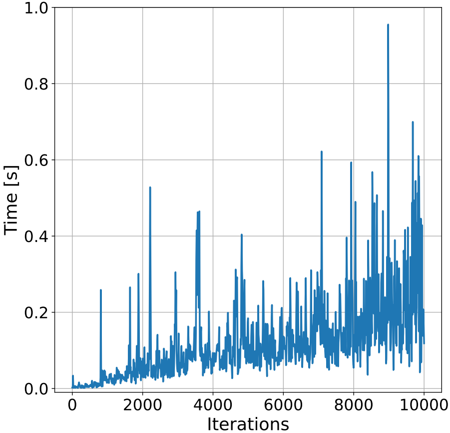
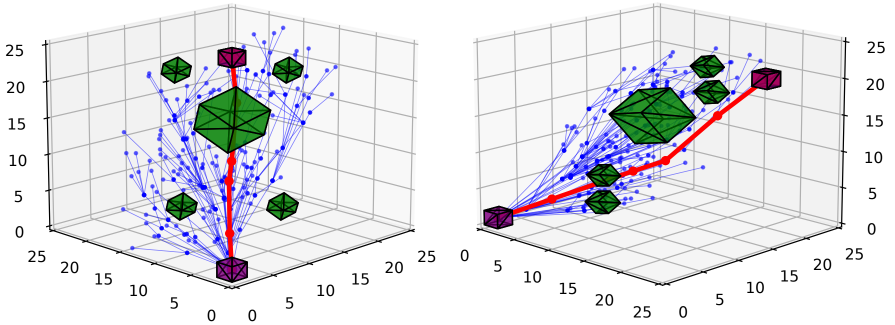


Figure: Time taken to learn predicting points in the 2D workspace with the 3D $\mathcal{C}$-space to be in the C_{free}.

Results



(a) RRT*_ML front view.

(b) RRT*_ML right view.

Figure: 6D $\mathcal{C}$-space.

Results

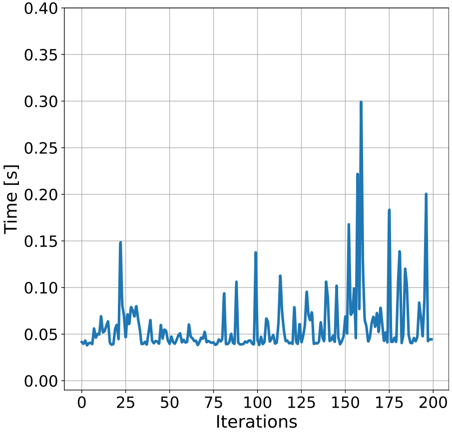


Figure: Time taken to learn predicting points in the 3D workspace with the 6D $\mathcal{C}$-space to be in the C_{free}.

Thanks for your attention!

Markus Rickert, Arne Sieverling, and Oliver Brock.
Balancing exploration and exploitation in sampling-based motion planning.
IEEE Transactions on Robotics, 30:1305–1317, 12 2014.