Informed Multi-Representation Multi-Heuristic A*

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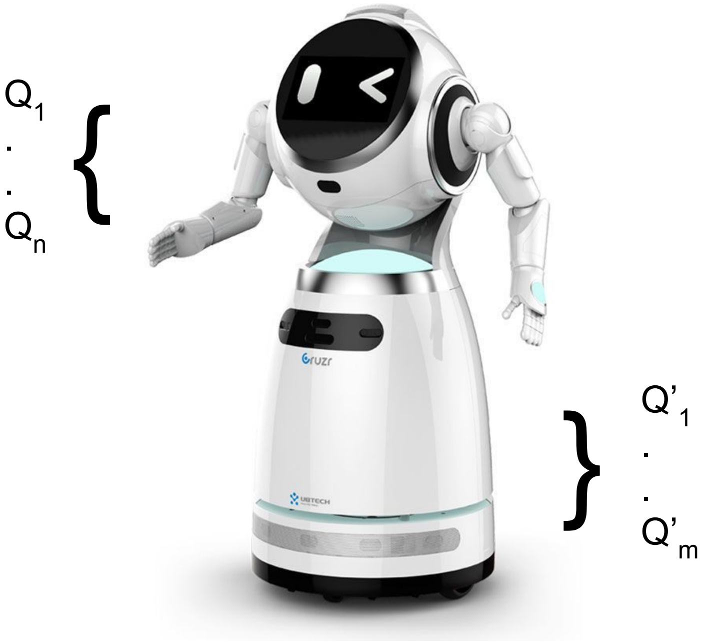
Motivation

MR-MHA*

+ exploits loose coupling between high dimensional state representations such as between the base and arm of a mobile manipulator
- is uninformed as base dimension and arm dimensions are always expanded alternately in a round-robin fashion



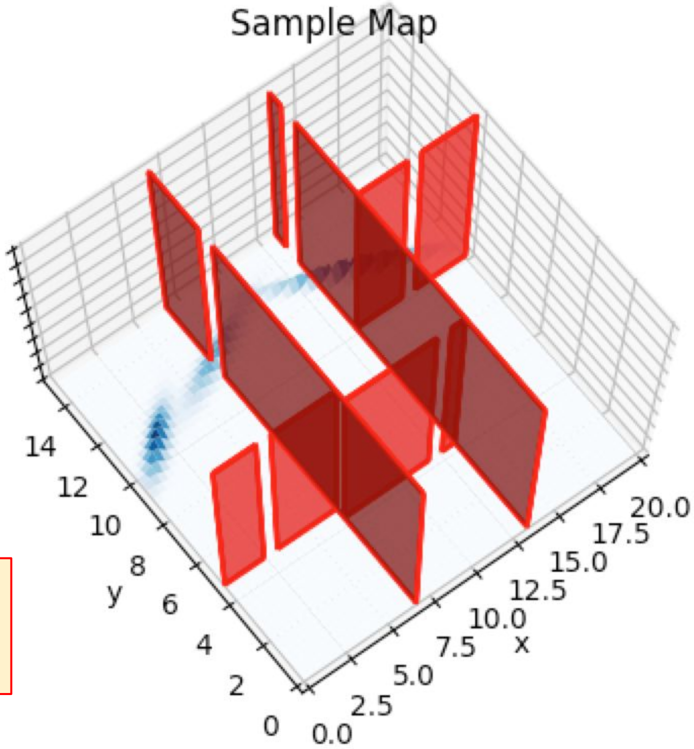
Youakim, D., Dornbush, A., Likhachev, M. and Ridao, P., 2018, October. Motion planning for an underwater mobile manipulator by exploiting loose coupling. In 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 7164-7171). IEEE.

Motivation

MR-MHA*

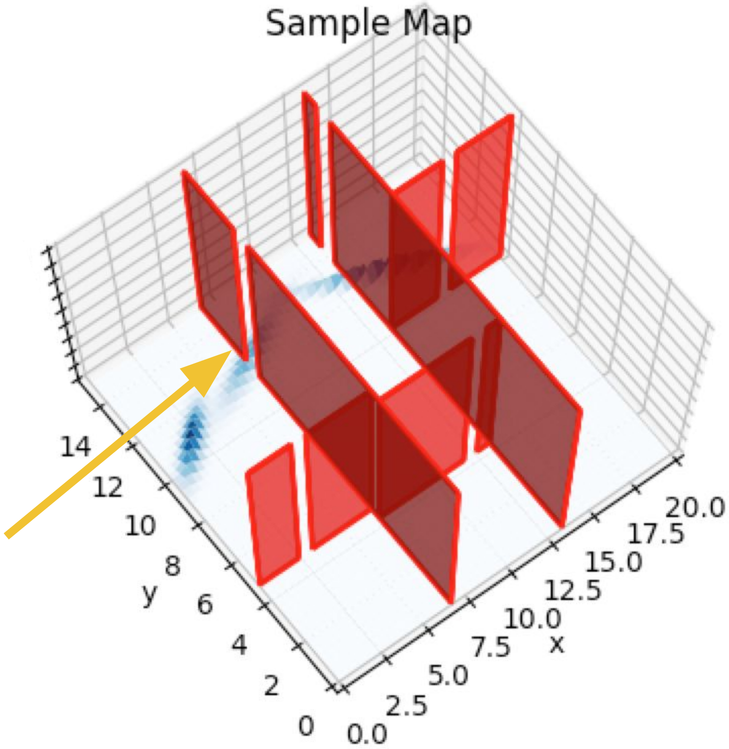
- \+ exploits loose coupling between high dimensional state representations such as between the base and arm of a mobile manipulator
- \- is uninformed as base dimensions and arm dimensions are always expanded alternately in a round-robin fashion

Can we learn a better expansion strategy to inform the search that incorporates knowledge of the environment?



Planning Representation

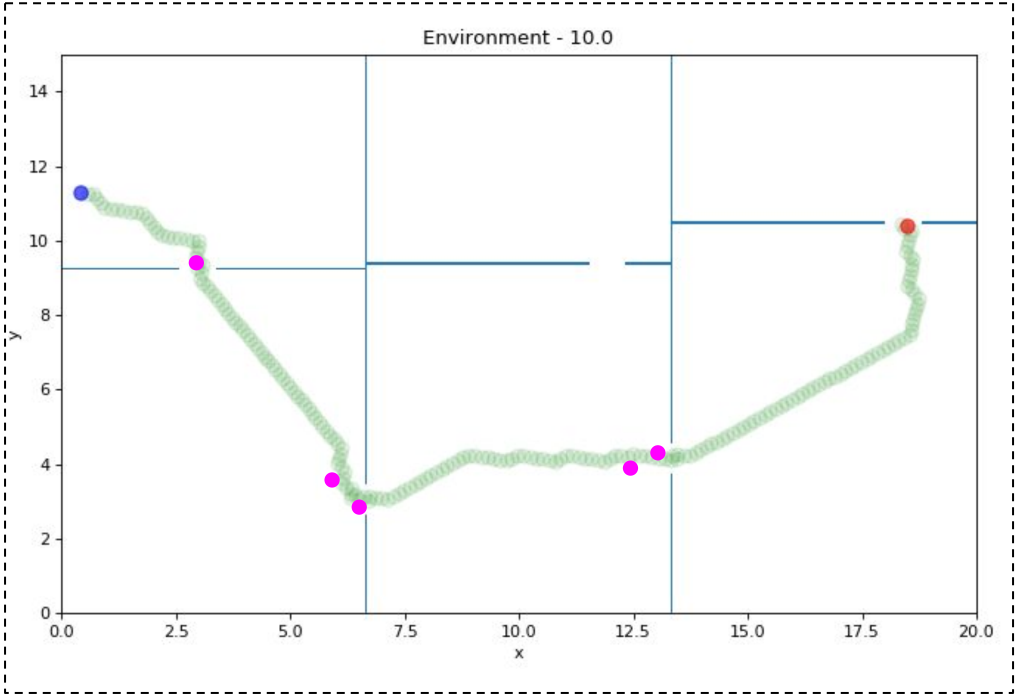
Robot State	$R = (R^A, R^B) \in \mathbb{R}^{10}$
Robot Arm Configuration	$R^A = (\theta_1, ..\theta_n) \in \mathbb{R}^7$
Robot Base Configuration	$R^B = (x, y, \psi) \in \mathbb{R}^3$
Robot State Start	$R_{start} = (R^A_{start}, R^B_{start})$
Robot State Goal	$R_{goal} = (R^A_{goal}, R^B_{goal})$
Position of Narrow Gaps	$\mathbb{N} = [(x_1, y_1)...(x_n, y_n)]$



Methodology

Training

Data Generation: Vanilla MRMHA*



Base Moved

Arm Moved

Methodology

Training

Data Generation: Vanilla MRMHA*

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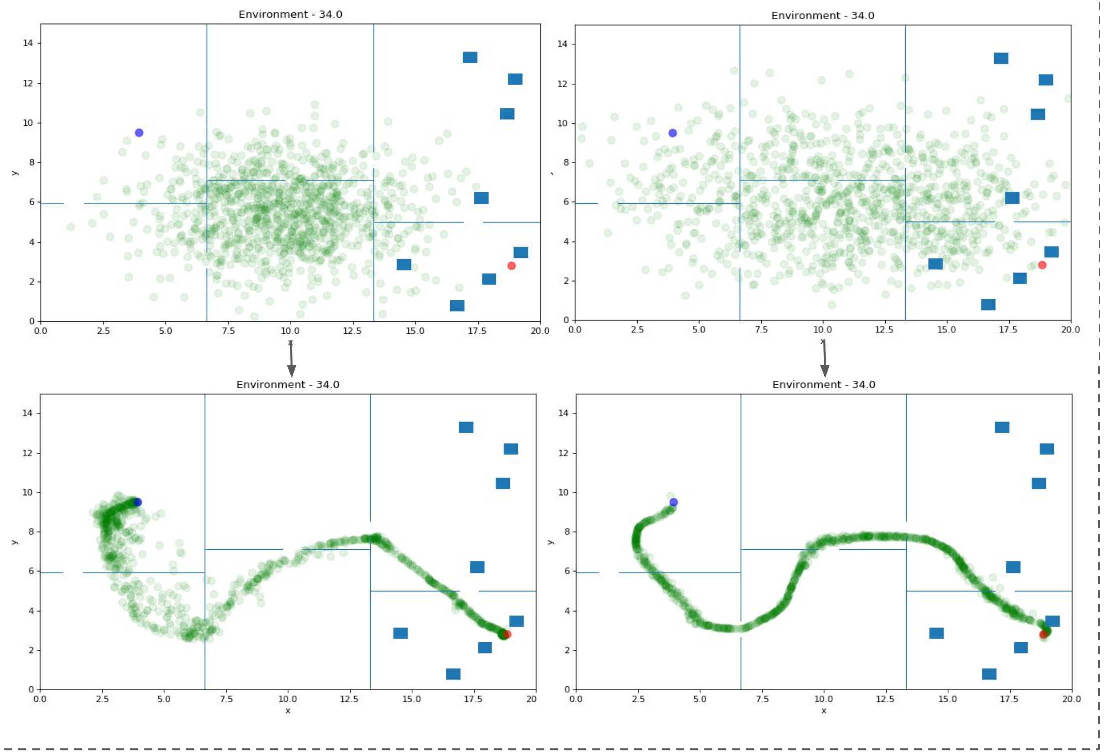
CVAE Training

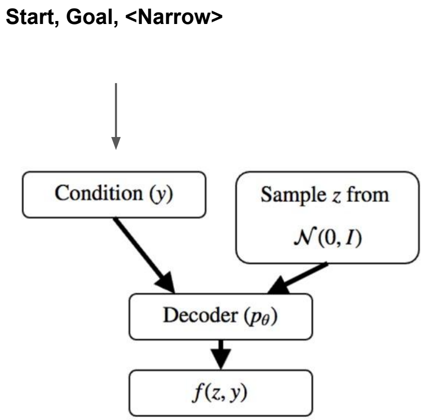
Arm

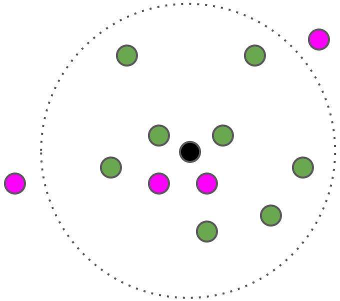
Base



Ichter, B., Harrison, J. and Pavone, M., 2018, May. Learning sampling distributions for robot motion planning. In 2018 IEEE International Conference on Robotics and Automation (ICRA) (pp. 7087-7094). IEEE.

Methodology





$$p(x) = \frac{\#arm}{\#arm + \#base}$$

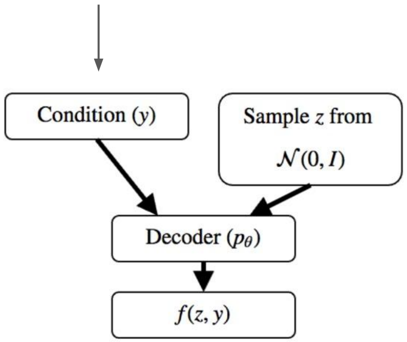
$$p(x) = \frac{\#base}{\#arm + \#base}$$

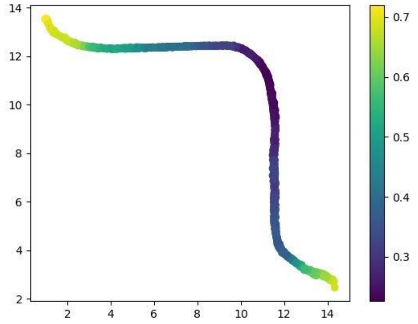
Testing

CVAE Inference

Methodology

Start, Goal, <Narrow>



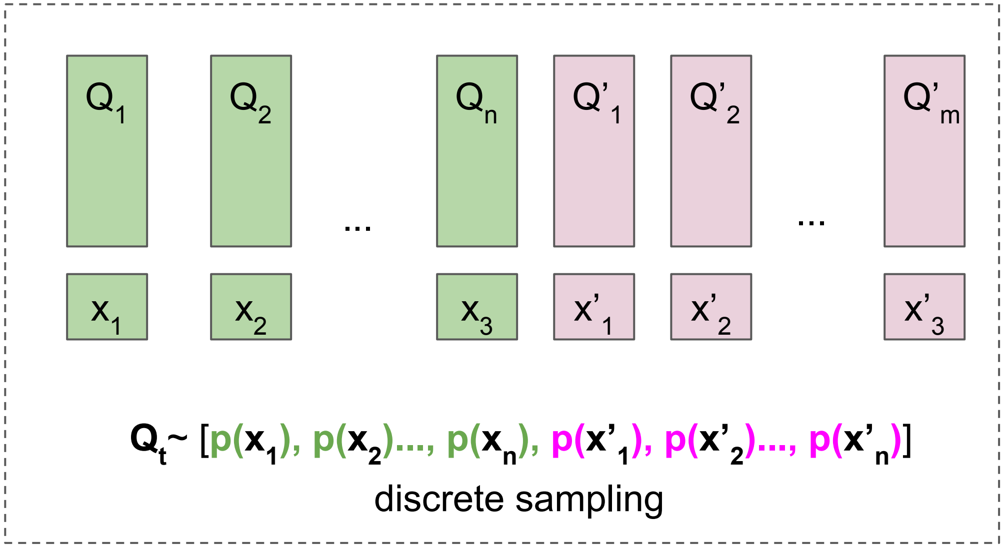


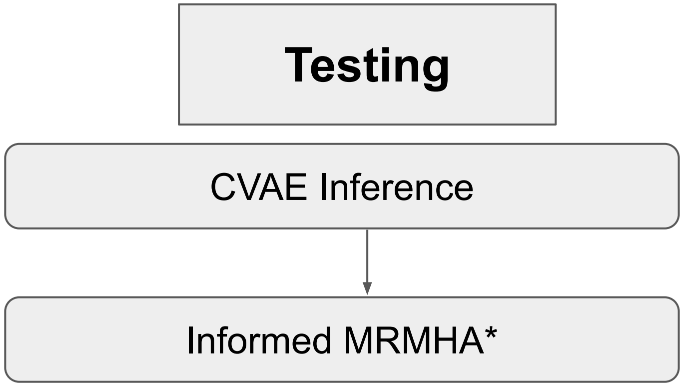
$p_{arm}(x)$

Testing

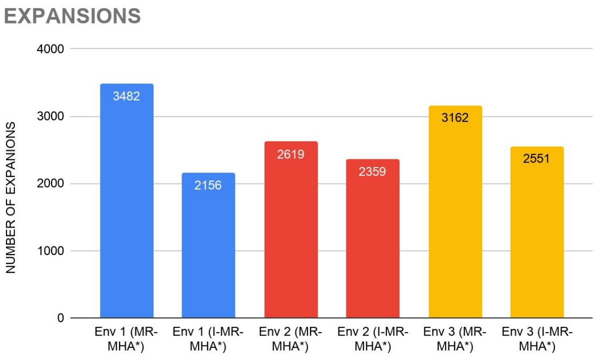
CVAE Inference

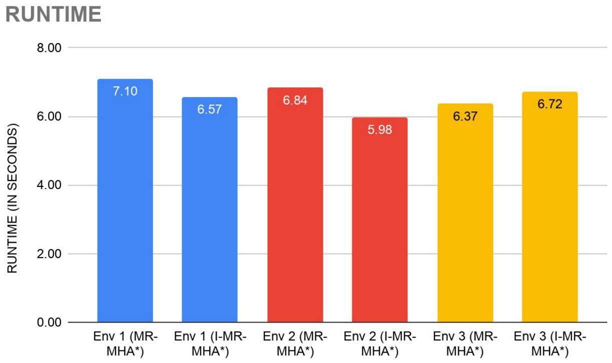
Methodology

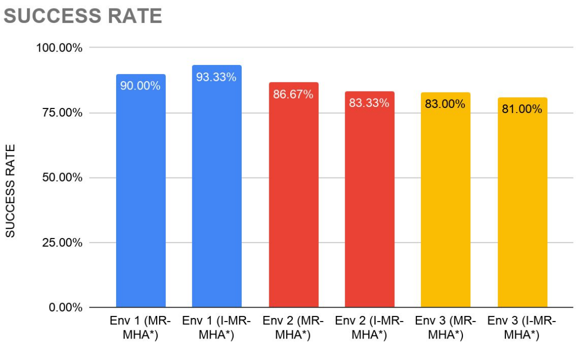




Results







- Mean Runtime Reduction ~ 5%: , Mean Expansion Reduction ~ 24.33%
- Significant runtime reduction in cases where CVAE produces samples covering the states explored by the heuristics well
- CVAE needs to be extended to cover whole map for more significant improvements (by learning from good expansions or under different conditioning)

DEMO