Learning Goal-Oriented Non-Prehensile Pushing in Cluttered Scenes

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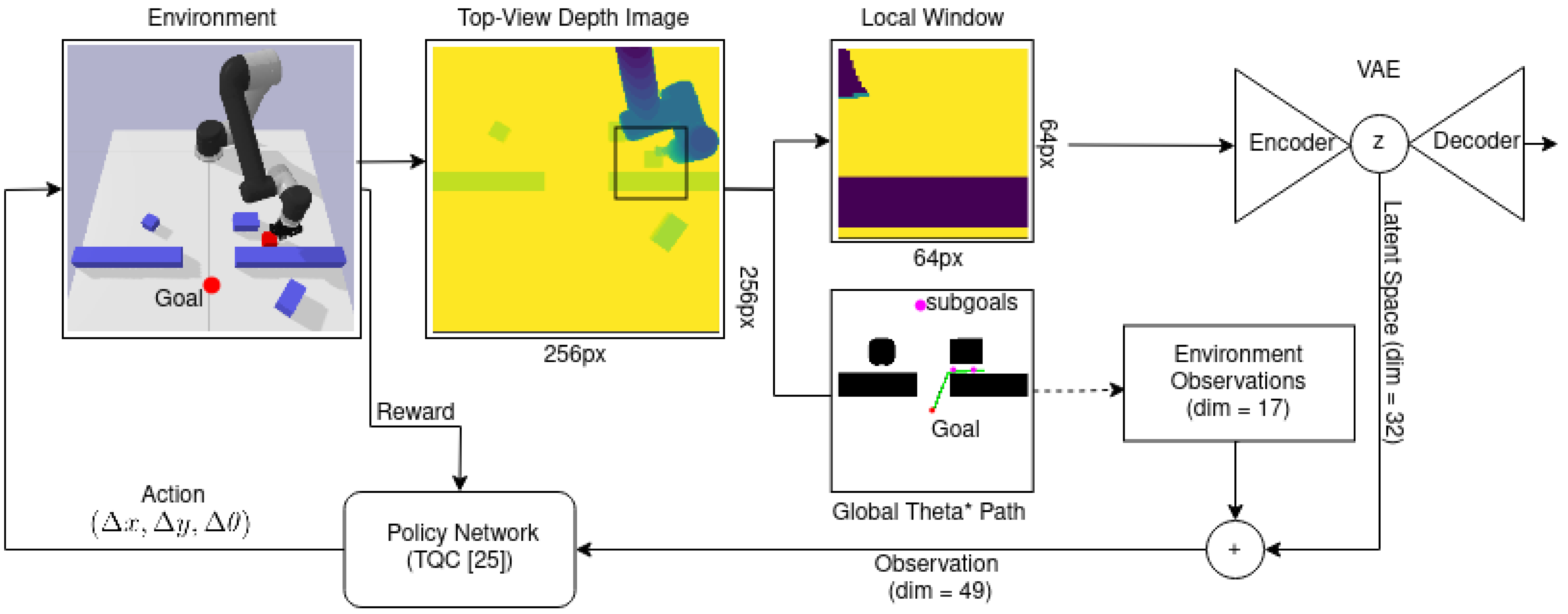
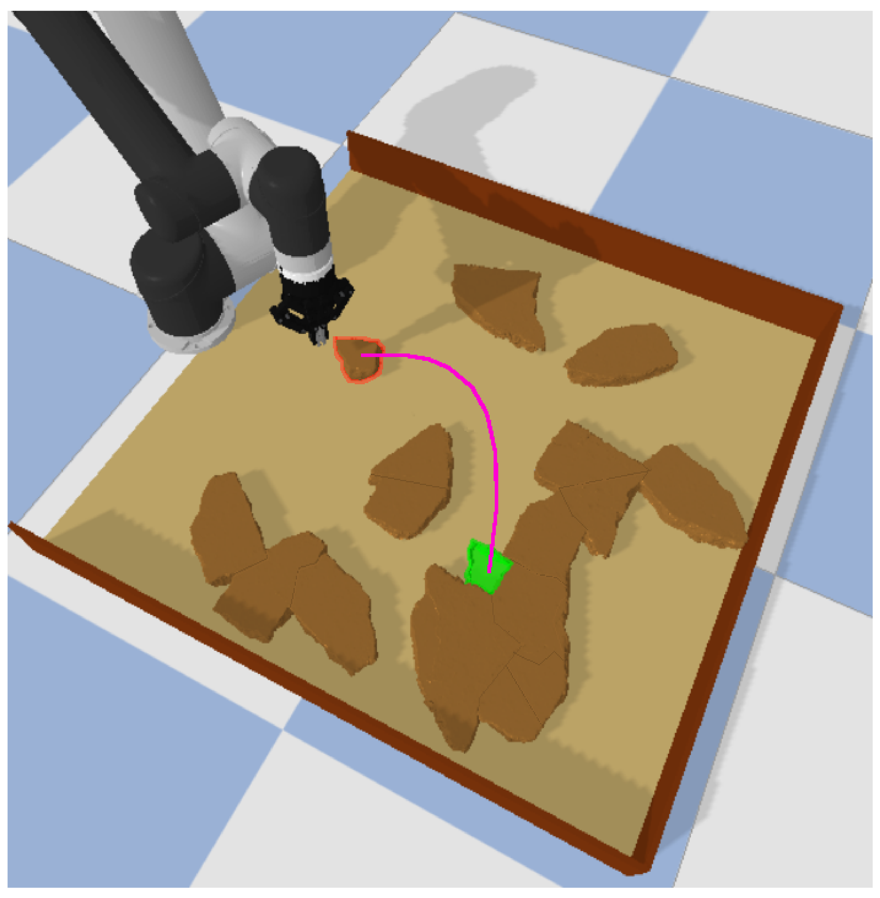
Overview



Motivation



- Goal-oriented contact-rich pushing behavior
- Sensitive towards clutter in the environment
- Smooth trajectories to ensure safe manipulation

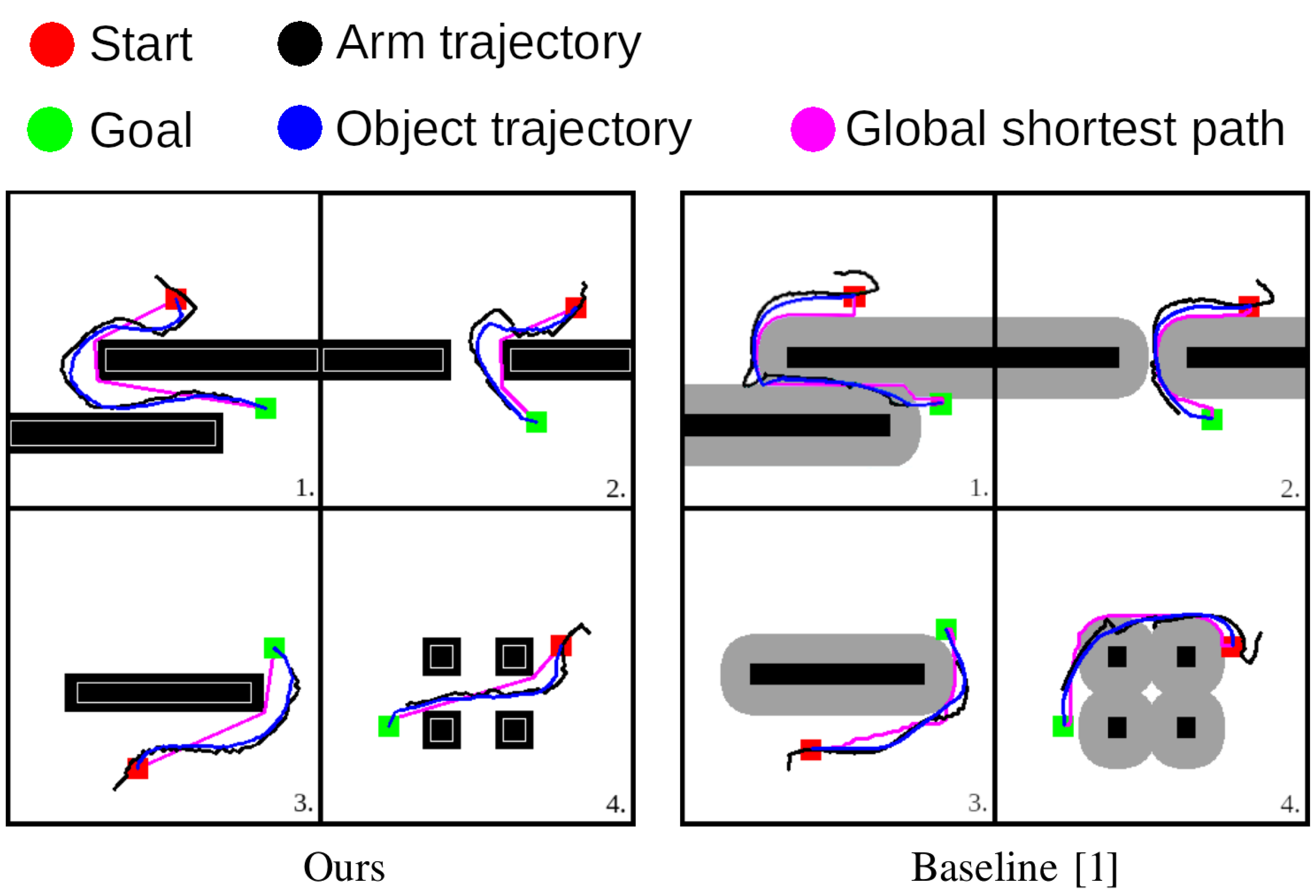
Our Approach

- Reinforcement learning: Truncated Quantile Critics
- Curriculum learning for better convergence
- Action space: EE pose change $(\Delta x, \Delta y, \Delta \theta)$
- Observation space:

observation	size
Local window latent space	32
EE position at t	5
6D joint angle poses	6
Sub-goal at t-1	2
Sub-goal at t-5	2
Contact with obstacle	1
Object to goal distance	1
Overall:	49

- Variational autoencoder to decouple the feature extraction process and obtain the latent space of the local window around the object

Qualitative Results: Example Paths



Quantitative Results

object avoidance	Success Rate	Object Contact Rate ⋆	Collision Rate ⋆	SPL ⋆	Path Length ⋆
Ours	**0.980**	**0.995** ± 0.02	**0.008** ± 0.04	0.910	0.523 ± 0.18
Krivic *et al.* [1]	0.955	0.850 ± 0.10	0.011 ± 0.05	**0.952**	**0.513** ± 0.16

Fragment	Success Rate	Object Contact Rate ⋆	Collision Rate ⋆	SPL ⋆	Path Length ⋆
Ours	0.867	0.980 ± 0.05	0.05 ± 0.11	0.71	0.630± 0.29
Ours re-trained	**0.959**	**0.984** ± 0.05	**0.01** ± 0.05	0.83	0.58± 0.23
Krivic *et al.* [1]	0.953	0.868± 0.11	0.024 ± 0.07	**0.951**	**0.501** ± 0.16

[1] Senka Krivic and Justus Piater.
Pushing corridors for delivering unknown objects with a mobile robot.
Autonomous Robots, 2019.

Summary

- Novel deep reinforcement learning approach for object pushing in cluttered tabletop environments
- Increased performance compared to [1] in terms of constant object contact and smooth trajectories
- The code of our system can be found at `https://github.com/NilsDengler/cluttered-pushing`