

How Does It Feel? Self-Supervised Costmap Learning for Off-Road Vehicle Traversability





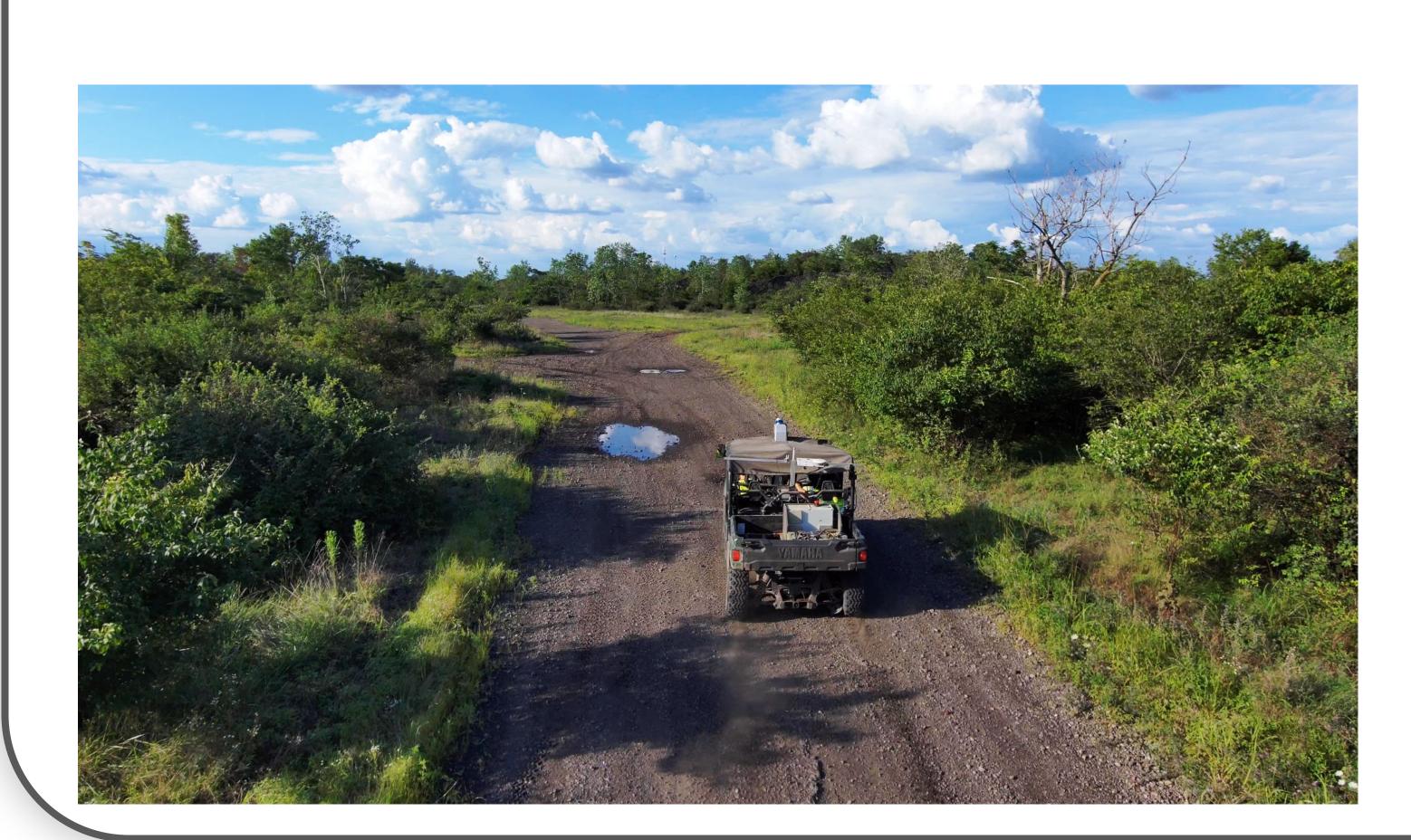
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1. Key Contributions

- 1. We introduce HDIF, a method that predicts continuous traversability costmaps from the robot's own proprioceptive terrain interaction feedback, without human annotated labels.
- 2. We demonstrate our method on short-scale and large-scale navigation trials on two different robot platforms: an autonomous Yamaha ATV and a Clearpath Warthog UGV.

For videos and more details, visit our website!





2. System Overview

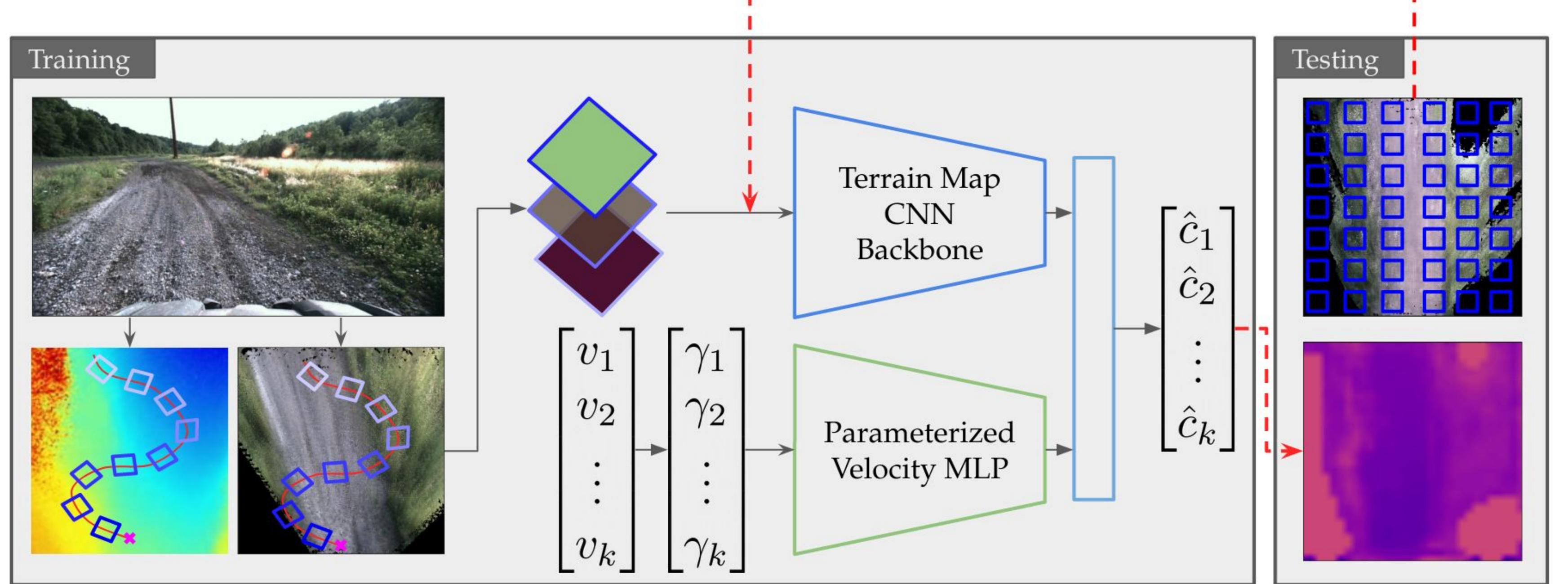
Training time:

- Patches cropped from a BEV RGB map and height map along the driving trajectory.
- Fourier-parameterized velocity per patch. Output:
- Continuous traversability cost for each

- L2 loss between predicted cost and pseudo ground-truth cost generated from IMU.

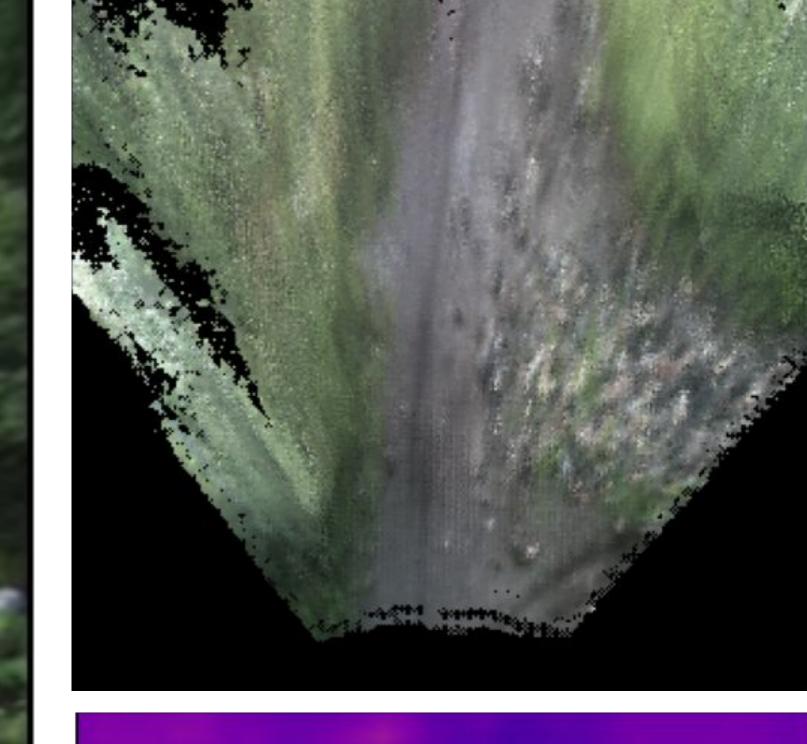
Test time:

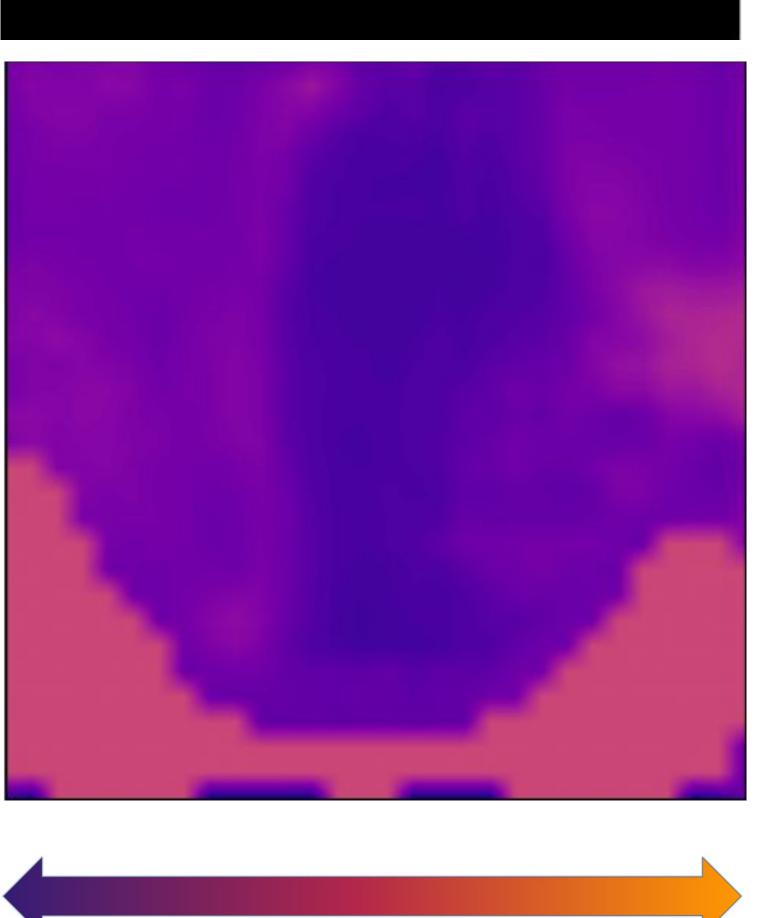
Subsample current map into small patches, then feed into the network to generate a continuous costmap.



4. Dataset and Output Costmaps







Low

Training set: TartanDrive (Triest et al., ICRA 2022)

BEV Mapping: Projected from dense point clouds from stereo images and registered using TartanVO (Wang et al., CoRL 2020).

Lower predicted cost:

- Packed dirt
- Concrete

Higher predicted cost:

- Vegetation
- Gravel
- Fallen leaves
- Logs

High

6. Navigation Results

Short-scale experiments: our robot prefers smoother

paths using our costmaps.

Large-scale experiments:

up to 57% fewer interventions than an occupancy-based navigation baseline.



Navigation Stack	Course	Num. Interventions	Approx. Course Length (m)
Baseline	Red	7	400
HDIF (Ours)	Red	3	400
Baseline	Blue	9	3150
HDIF (Ours)	Blue	6	3150
Baseline	Green	11	950
HDIF (Ours)	Green	7	950