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

Mateo Guaman Castro[1], Samuel Triest[1], Wenshan Wang[1], Jason M. Gregory[2], Felix Sanchez[3], John G. Rogers III[2], Sebastian Scherer[1]

[1]Carnegie Mellon University [2]Army Research Lab [3]Booz Allen Hamilton

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

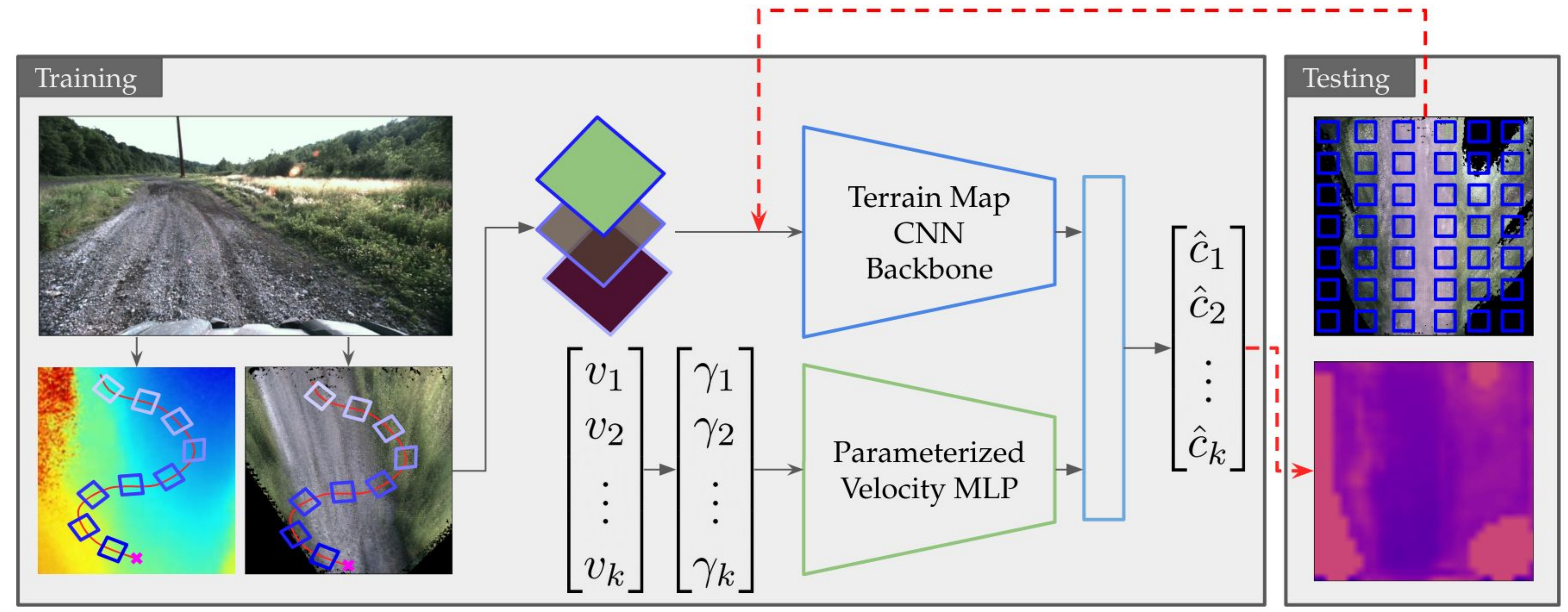
Training time:

Input:
- Patches cropped from a BEV RGB map and height map along the driving trajectory.
- Fourier-parameterized velocity per patch.

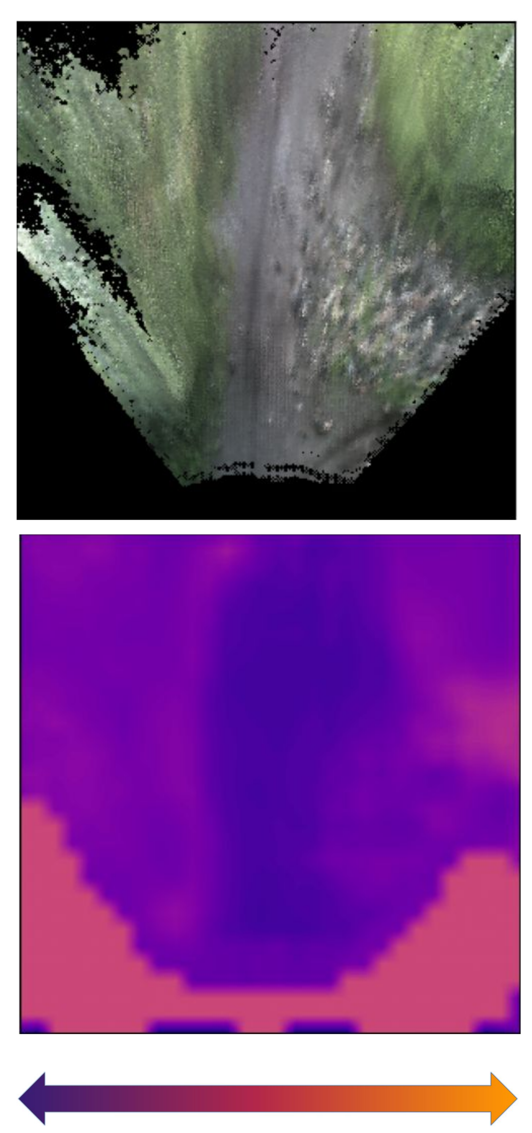
Output:
- Continuous traversability cost for each patch

Loss:
- 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.



3. Dataset and Output Costmaps



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

4. 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

Contact: mguamanc@andrew.cmu.edu @mateoguaman

Website: mateoguaman.github.io/hdif