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

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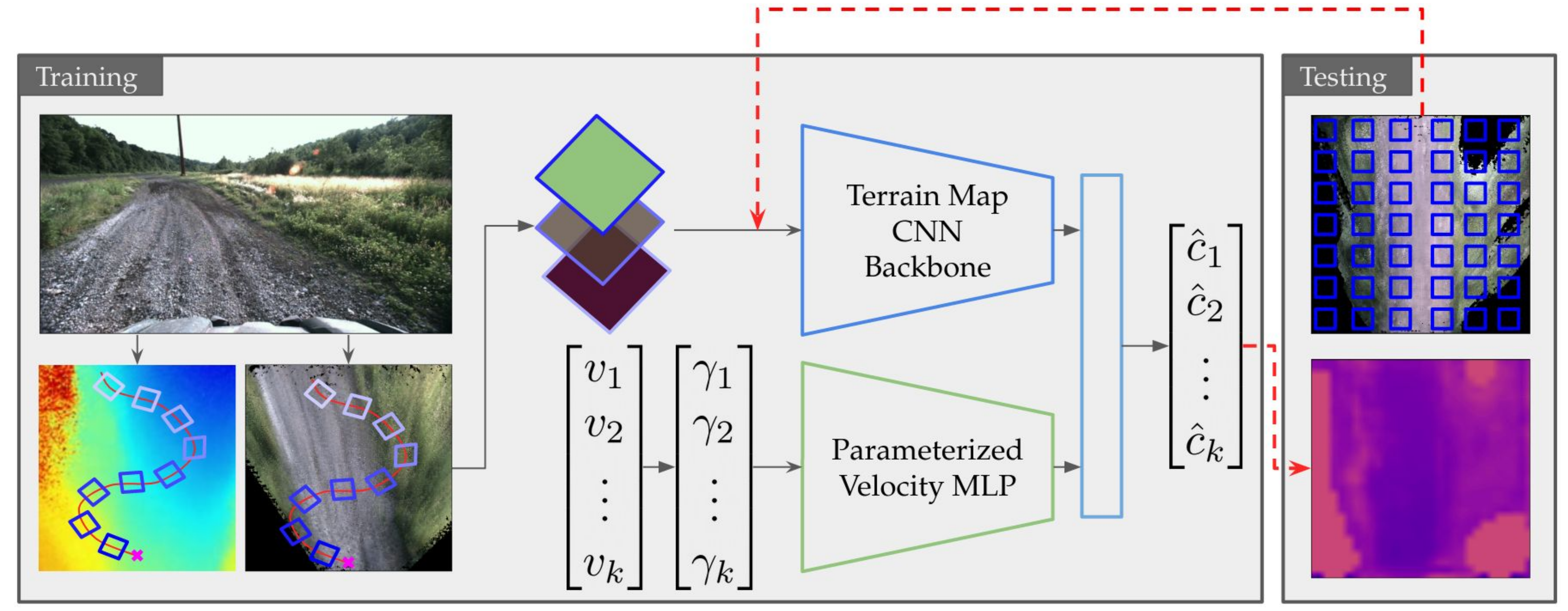
1. At a Glance

1. We introduce HDIF, a method that predicts continuous traversability costmaps from the robot's own proprioceptive terrain interaction feedback.
2. Our method is scalable, since it does not require expensive, hand-engineered semantic labels, or carefully-tuned geometric thresholds to predict traversability in off-road environments.

2. System Overview



During training, the network takes in patches cropped from a top-down colored map and height map along the driving trajectory, and the parameterized velocity for each patch.

The network predicts a traversability cost for each patch, supervised by a pseudo ground-truth cost generated from IMU.

During testing, the whole map is subsampled into small patches, which are fed into the network to generate a continuous costmap.

3. Key Contributions

1. Our method learns to predict continuous-valued costmaps from BEV visual, geometric, and velocity information, without human-annotated labels.
2. We present an IMU-derived traversability cost that can be used as a self-supervised pseudo ground-truth for training.
3. 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 detailed information of our experiments, visit our website!

4. Dataset and Mapping

We use TartanDrive (Triest et al., ICRA 2022) for training, from which we extract 15K training frames, and 3K validation frames.

We fine-tune the base model with 9.5K training frames and 1.3K validation frames for our Warthog experiments.

We obtain BEV RGB and height maps from dense point clouds generated from stereo images and registered using TartanVO (Wang et al, CoRL 2020).

5. Output Costmaps

We produce costmaps by taking the current local map in front of the robot, extracting patches at uniformly sampled positions, and passing them through the network.

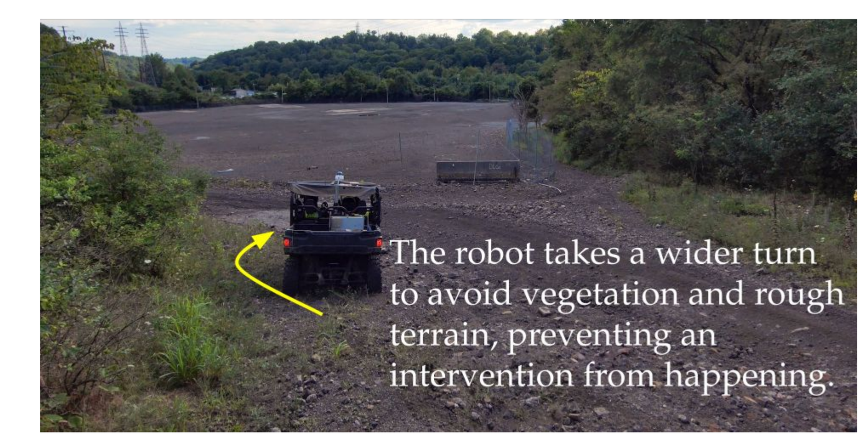
Our costmaps show that vegetation and trail features such as gravel, fallen leaves, and smalls obstacles, such as logs, have a higher predicted cost than smoother trails or concrete.

Lower Cost　　Higher Cost

6. Navigation Results

In short-scale navigation experiments, our robot prefers smoother paths using our costmaps.

In large-scale navigation courses, we achieve 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

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