Proprioception Is All You Need: Terrain Classification for Boreal Forests

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WhoAmI

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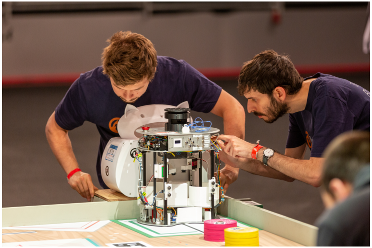

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Field deployments in *Forêt Montmorency*

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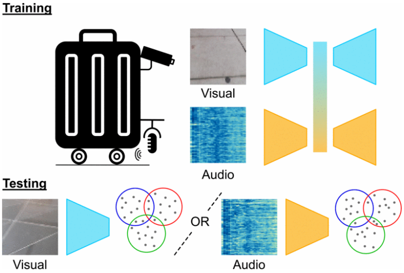
Challenging terrains in *Forêt Montmorency*

(a) In deep snow (b) In peat moss

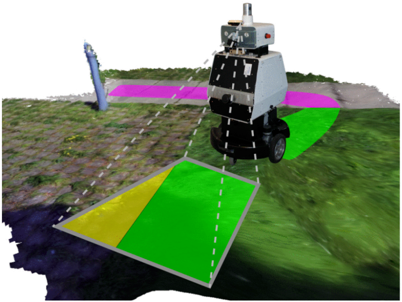
Figure 1: Issues encountered during autonomous driving experiments

Overview

Context



(a) Ishikawa *et al.* [1]



(b) Zürn *et al.* [2]

Figure 2: Audiovisual-based terrain classification (TC)

Context

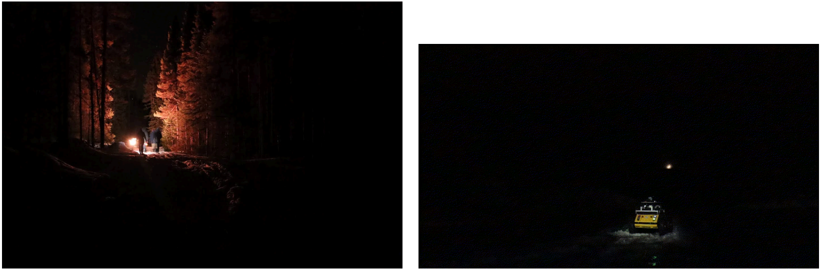


Figure 3: Dark conditions in *Forêt Montmorency*

Context

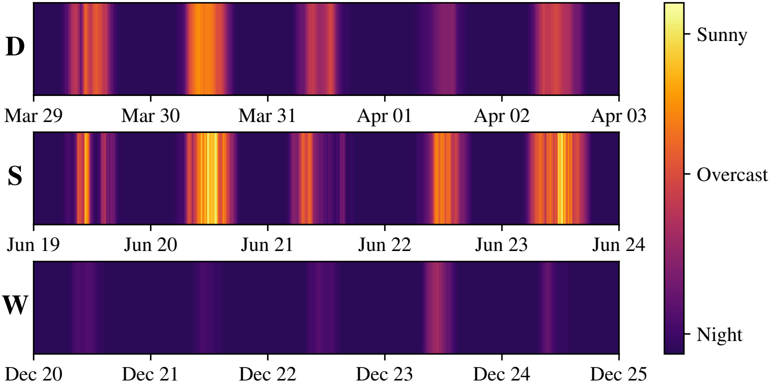


Figure 4: Hourly sun radiation measurements in *Forêt Montmorency* for three distinct weeks. (**D**): Deployment week, (**S**): 2021 summer solstice, (**W**) 2020 winter solstice [3].

Context

Figure 5: Experiment during a heavy snowstorm in Quebec City, Canada [4].

Context

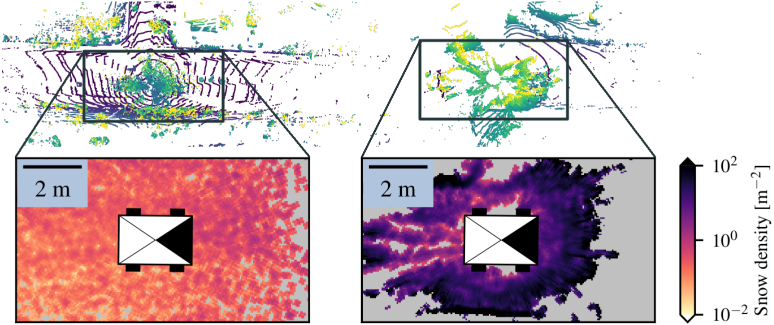


Figure 6: Examples of snow density fields with their associated point clouds. Left: Weak snowstorm. Right: Heavy snowstorm with a snow gust [4].

Context

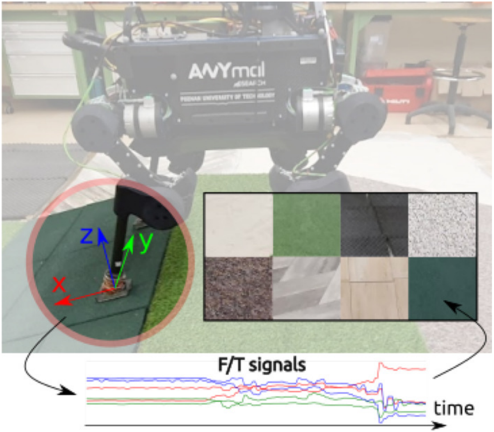


Figure 7: Haptic-based TC for legged robots [5]

Context

Figure 8: Proprioceptive-based TC for wheeled robots [6]

BorealTC dataset for terrain classification (TC)

- Recorded with a `Husky A200` from *Clearpath Robotics* (Kitchener, Ontario, Canada).
- 116 min of proprioceptive measurements
  - Wheel service (motor currents and wheel velocities) @ 6.5 Hz.
  - Xsens MTi-30 IMU (6-DOF angular velocities and linear accelerations) @ 100 Hz.

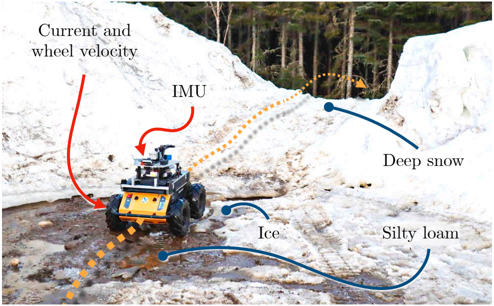
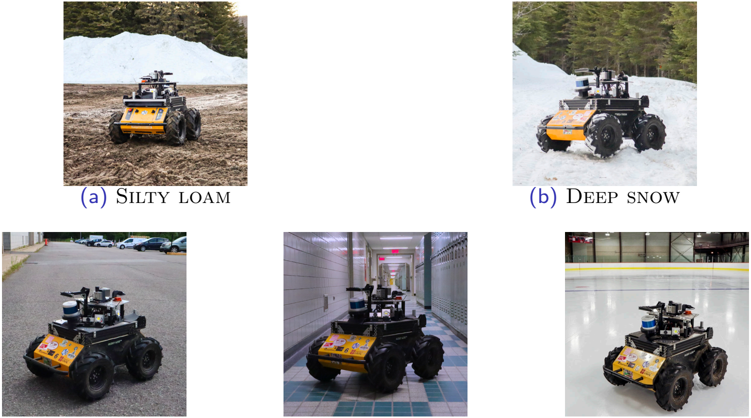


Figure 9: An example of challenges caused by terrain in boreal forests.

Terrains considered in BorealTC



(a) Silty loam (b) Deep snow

(c) Asphalt (d) Flooring (e) Ice

Figure 10: Types of terrains considered in our dataset.

Our Approach

`BorealTC` was combined with the `Vulpi` dataset from Vulpi *et al.* [6]: 13 min of data on four different terrains on a experimental farm in San Cassiano 🇮🇹 .

Terrain classification was evaluated with:

- a Convolutional Neural Network (CNN) classifier [6];
- the state space model (SSM)-based Mamba architecture [7], [8].

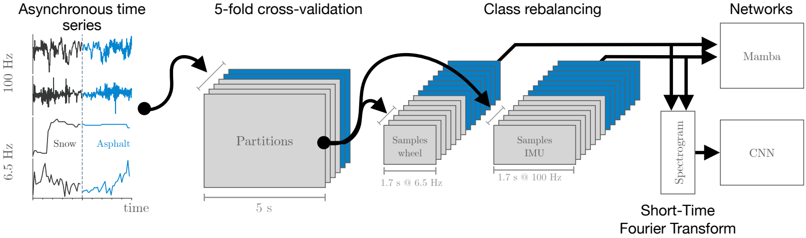


Figure 11: Overview of the training process.

Results

Models Performance

Table 1: Vulpi dataset (13 min).

Terrain	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
CNN				
Concrete	**99.21**	**95.27**	**97.20**	**94.12**
Dirt Road	**92.40**	**92.05**	**92.22**	
Ploughed	**96.94**	**98.96**	**97.94**	
Unploughed	**88.20**	**90.48**	**89.32**	
Mamba				
Concrete	87.13	83.33	85.19	86.76
Dirt Road	91.34	83.90	87.46	
Ploughed	93.93	96.67	95.28	
Unploughed	76.08	83.93	79.81	

Results

Models Performance

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Terrain	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
		CNN		
Concrete	**99.21**	**95.27**	**97.20**	**94.12**
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		Mamba		
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Dirt Road	91.34	83.90	87.46	
Ploughed	93.93	96.67	95.28	
Unploughed	76.08	83.93	79.81	

Table 2: `BorealTC` dataset (116 min).

Terrain	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
		CNN		
Asphalt	**92.98**	83.89	88.20	**93.96**
Flooring	**97.29**	**98.70**	**97.99**	
Ice	**97.25**	**98.11**	**97.68**	
Silty Loam	**96.00**	**97.24**	**96.61**	
Snow	86.84	**92.31**	89.49	
		Mamba		
Asphalt	91.90	**85.50**	**88.59**	93.68
Flooring	95.46	98.17	96.79	
Ice	97.12	97.36	97.24	
Silty Loam	95.39	96.20	95.79	
Snow	**88.68**	91.57	**90.10**	

Results

Train dataset size ablation study

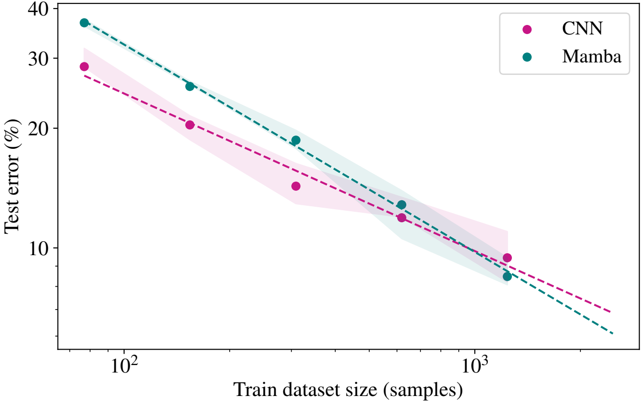
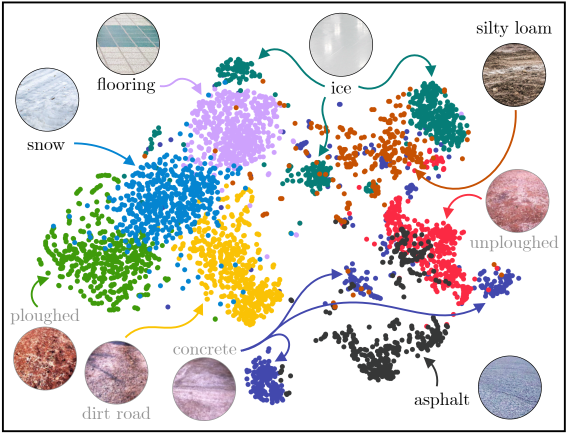


Figure 12: Influence of train dataset size on the test error in log-log scale.

Results

Latent space between the BorealTC and Vulpi [6] datasets



Results

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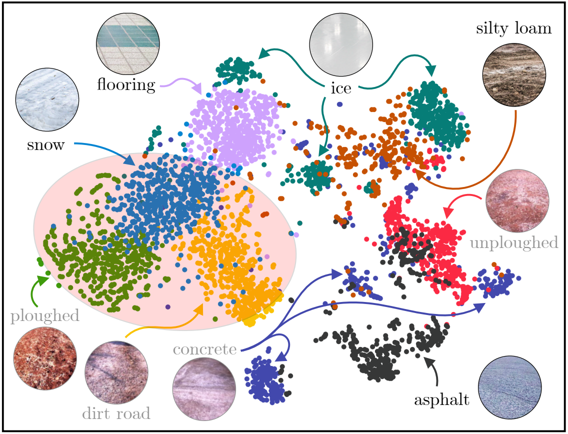

Results

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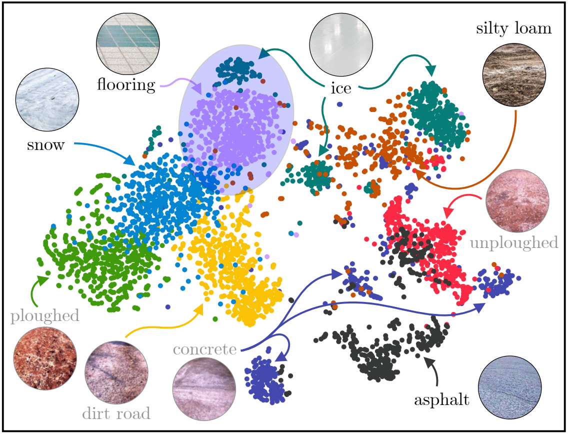

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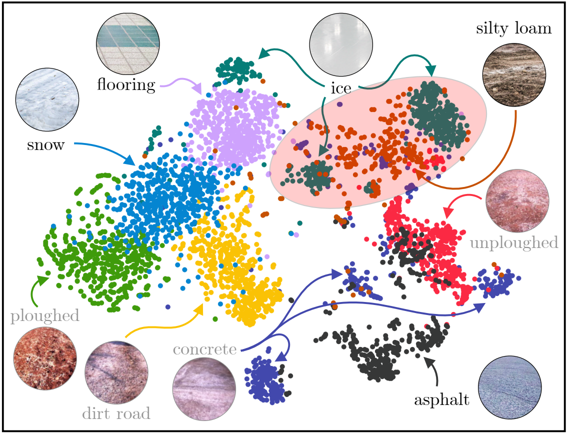

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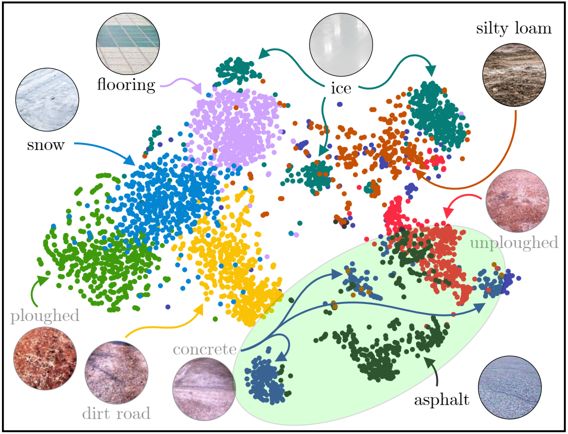

Contributions

- `BorealTC` dataset for terrain classification in boreal forests.
- Improvement on CNNs methods for data-driven terrain classification.
- Exploration of SSM-based approaches for terrain classification.
- Assessment of terrain classes on a combined terrain classification dataset.

Future Research

- Compare with other sensor modalities [9].
- Compare with other architectures.
- Extend the dataset.
  - Standardize the data acquisition procedure
  - Deploy a standard vehicle platform in various biomes
  - Combine the datasets from different vehicles
- Expand to terrain characterization [10].

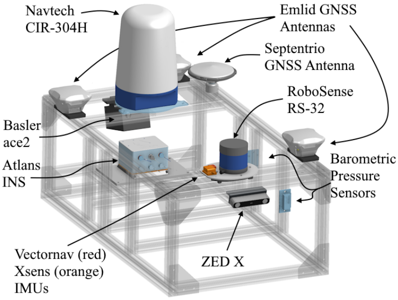

Figure 13: Sensor modality for the proposed *Forêt Montmorency* Dataset [9].

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[7] A. Gu and T. Dao, "Mamba: Linear-Time Sequence Modeling with Selective State Spaces," *arXiv preprint arXiv:2312.00752*, Dec. 2023.

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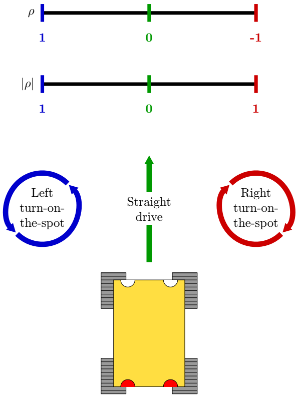
BorealTC vs Vulpi [6] datasets

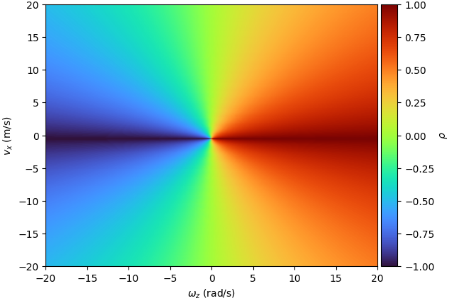
Table 3: Description of both datasets. SC: San Cassiano, FM: *Forêt Montmorency*.

Terrain	N	Loc.	$\lvert\tilde{v}_x\rvert\,(IQR)$	$\lvert\tilde{\omega}_z\rvert\,(IQR)$
		Vulpi [6]		
Concrete	24	SC	0.56 (0.26)	0.00 (0.00)
Dirt Road	16	SC	0.56 (0.25)	0.00 (0.00)
Ploughed	60	SC	0.56 (0.26)	0.00 (0.00)
Unploughed	56	SC	0.56 (0.25)	0.00 (0.00)
		BorealTC (ours)		
Asphalt	111	UL	0.46 (0.58)	0.01 (0.09)
Flooring	423	UL	0.23 (0.05)	0.02 (0.09)
Ice	450	UL	0.24 (0.38)	0.27 (0.52)
Silty Loam	126	FM	0.00 (0.24)	0.10 (0.17)
Snow	281	FM	0.00 (0.31)	0.10 (0.26)

Rotationality



$$\rho = \frac{B\omega_z}{|v_x| + B|\omega_z|}, \quad (1)$$



Rotationality

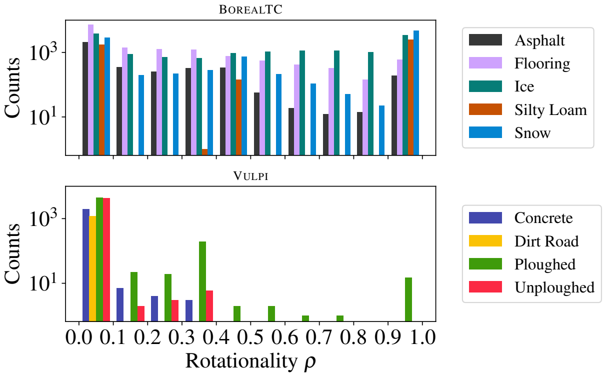


Figure 14: Distributions of rotationality of both datasets, from purely linear motions $(\rho = 0)$ to purely rotational motions $(\rho = 1)$.