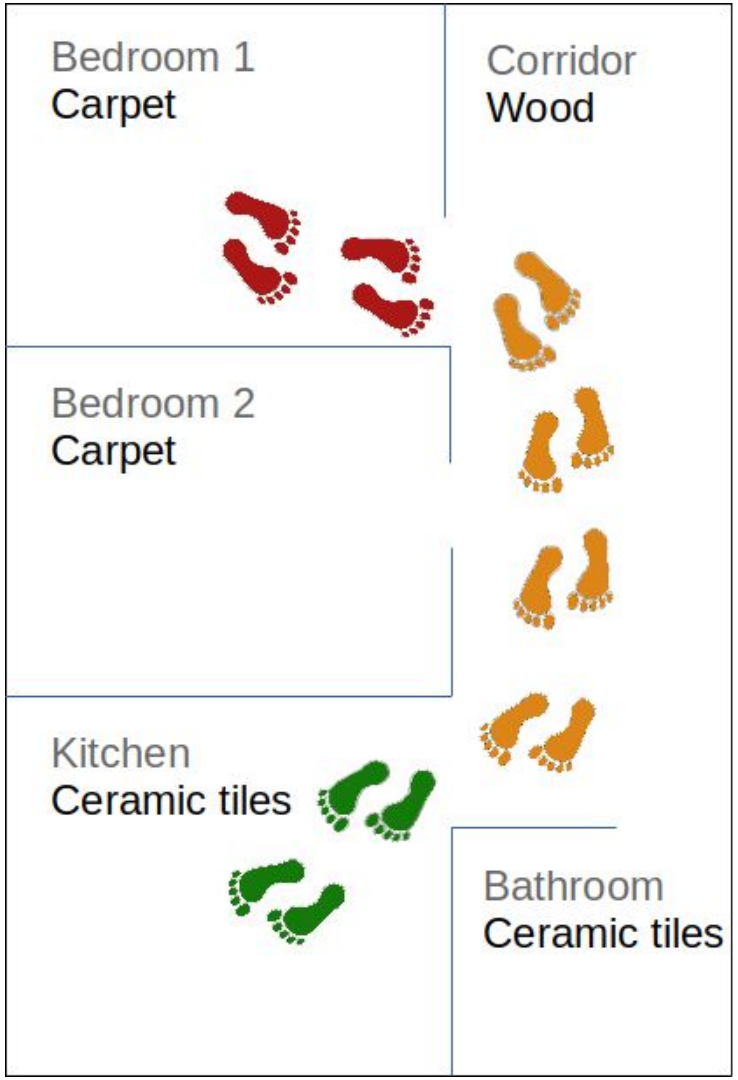
Haptic Monte Carlo Localisation for a Legged Robot

Michał Nowicki, PhD

Night mission to the kitchen

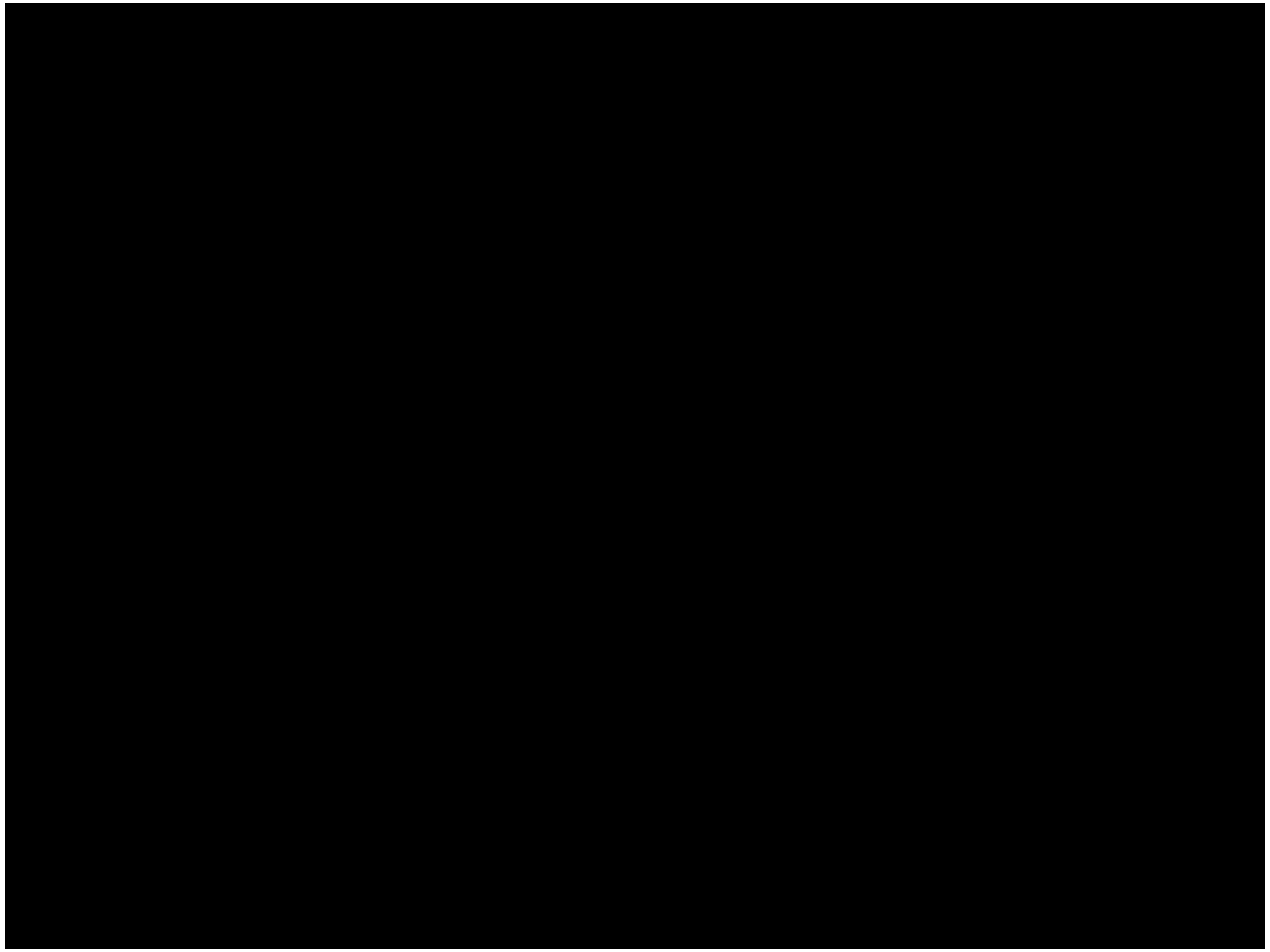
- You wake up in the middle of the night.
- You need to get some water from the kitchen.
- You know the map of your flat.
- You don't want to turn on the light not to wake others up.
- You are walking barefoot, so you can sense the materials on the floor.



Industrial application

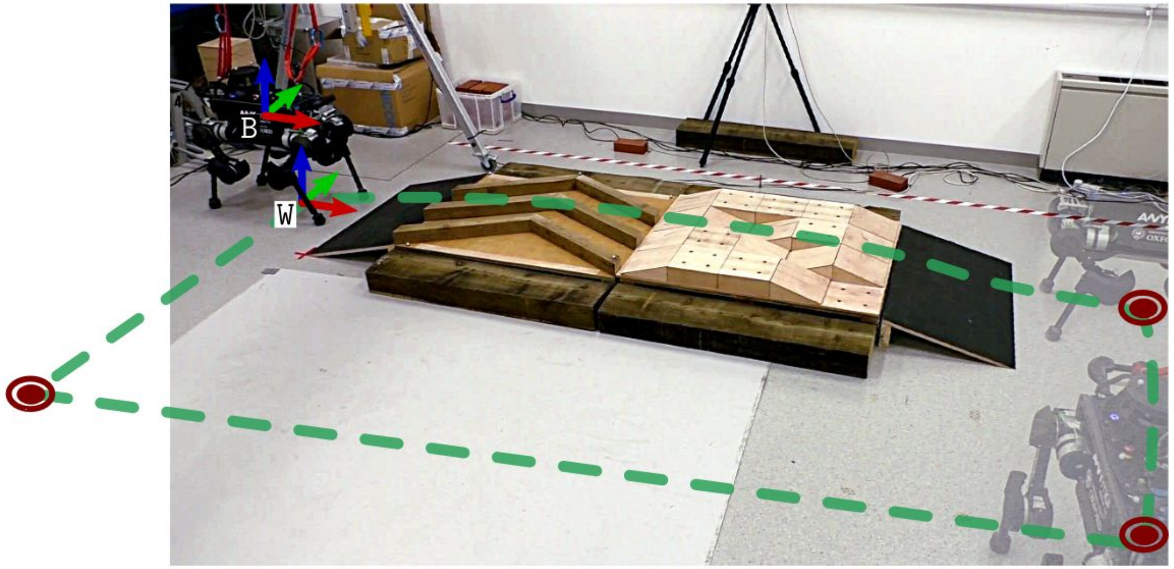
- Repeatable inspections in hot, humid, challenging environments where it is better to send a robot than a person.
- In these conditions, vision/LiDARs might fail.
- We need additional robustness to be able to deploy it.

Industrial application



Inspiration

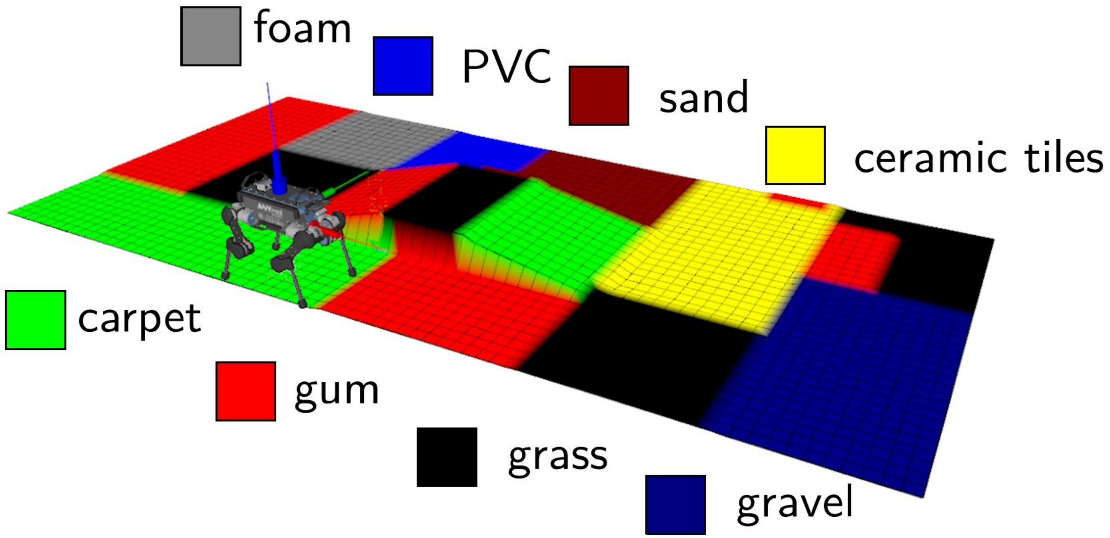
- Localization with known, dense, 2.5D height map of the environment.
- Utilizing particle filter to estimate the state of the walking robot.
- Using robot's odometry and step height to provide localization.

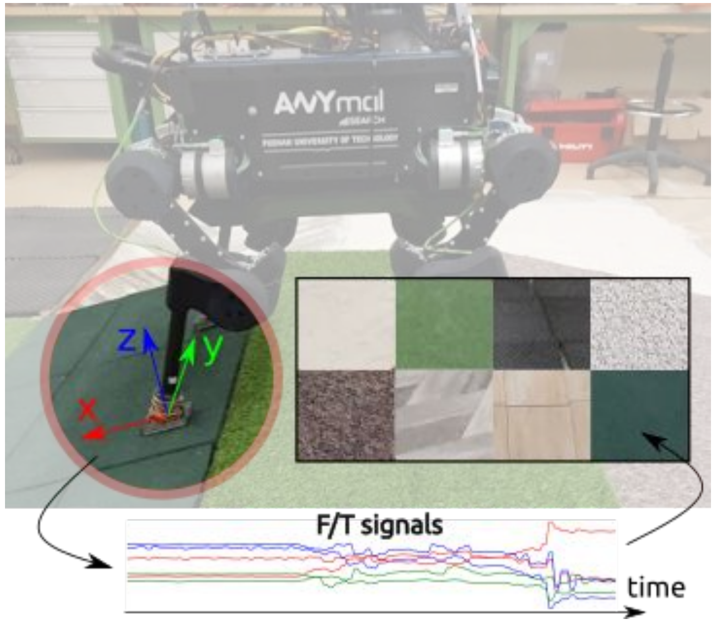


R. Buchanan, M. Camurri, M. Fallon, Haptic Sequential Monte Carlo Localization for Quadrupedal Locomotion in Vision-Denied Scenarios, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020.

Problem statement

- Given a quadruped robot with 12 active DoF.
- We want to localize the robot against a prior map blindly.
- Given legged odometry and the force/torque (F/T) signals from the feet.

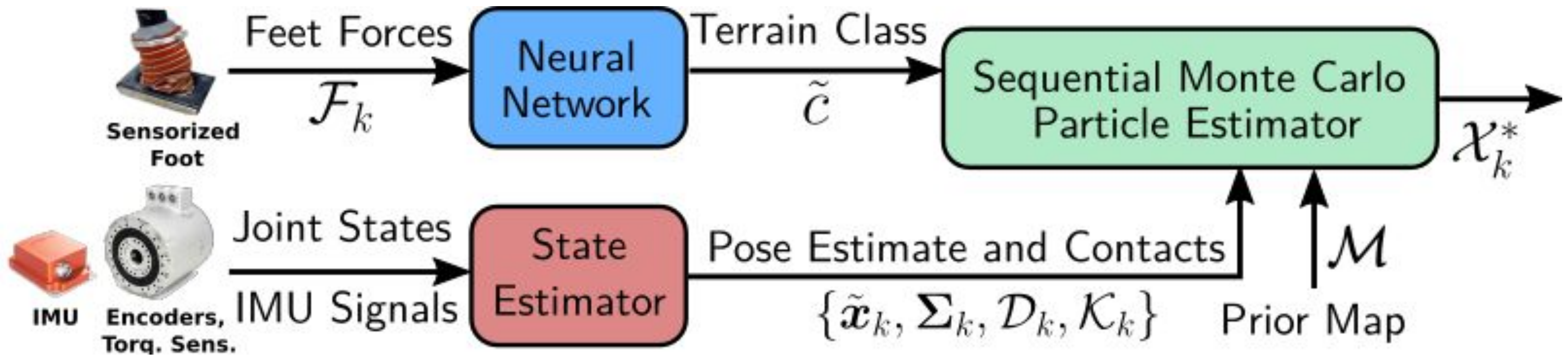




Evaluation setup

We gathered our dataset with an accurate 3D map (construction-grade 3D LiDAR) and precise feet positions (Optitrack)

Localization with Terrain Classification



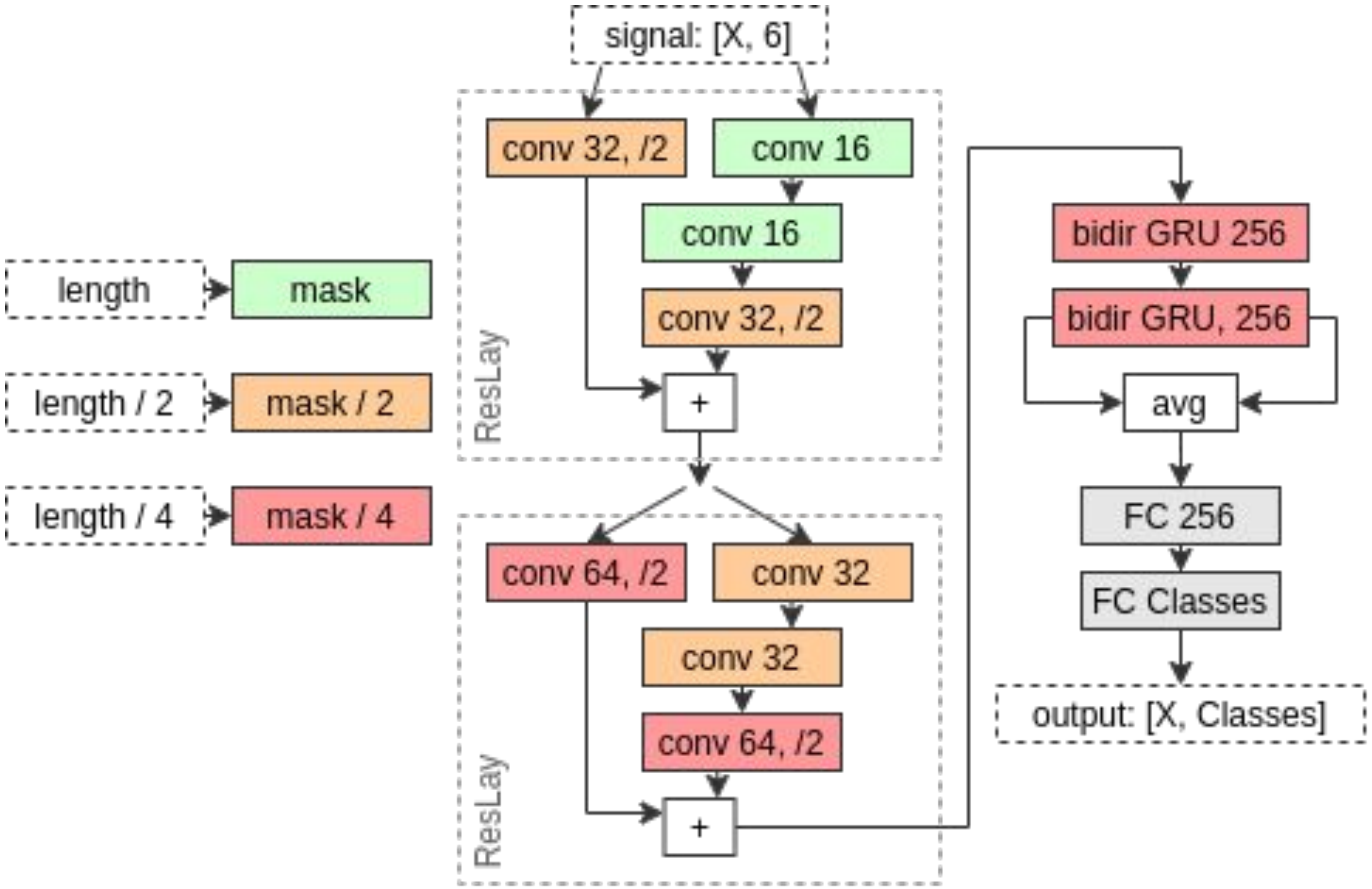
Requirements:

- dense 2.5D height map with terrain class annotations.

R. Buchanan, J. Bednarek, M. Camurri, M. R. Nowicki, K. Walas, and M. Fallon, Navigating by touch: Haptic monte carlo localization via geometric sensing and terrain classification, Autonomous Robots, 2021

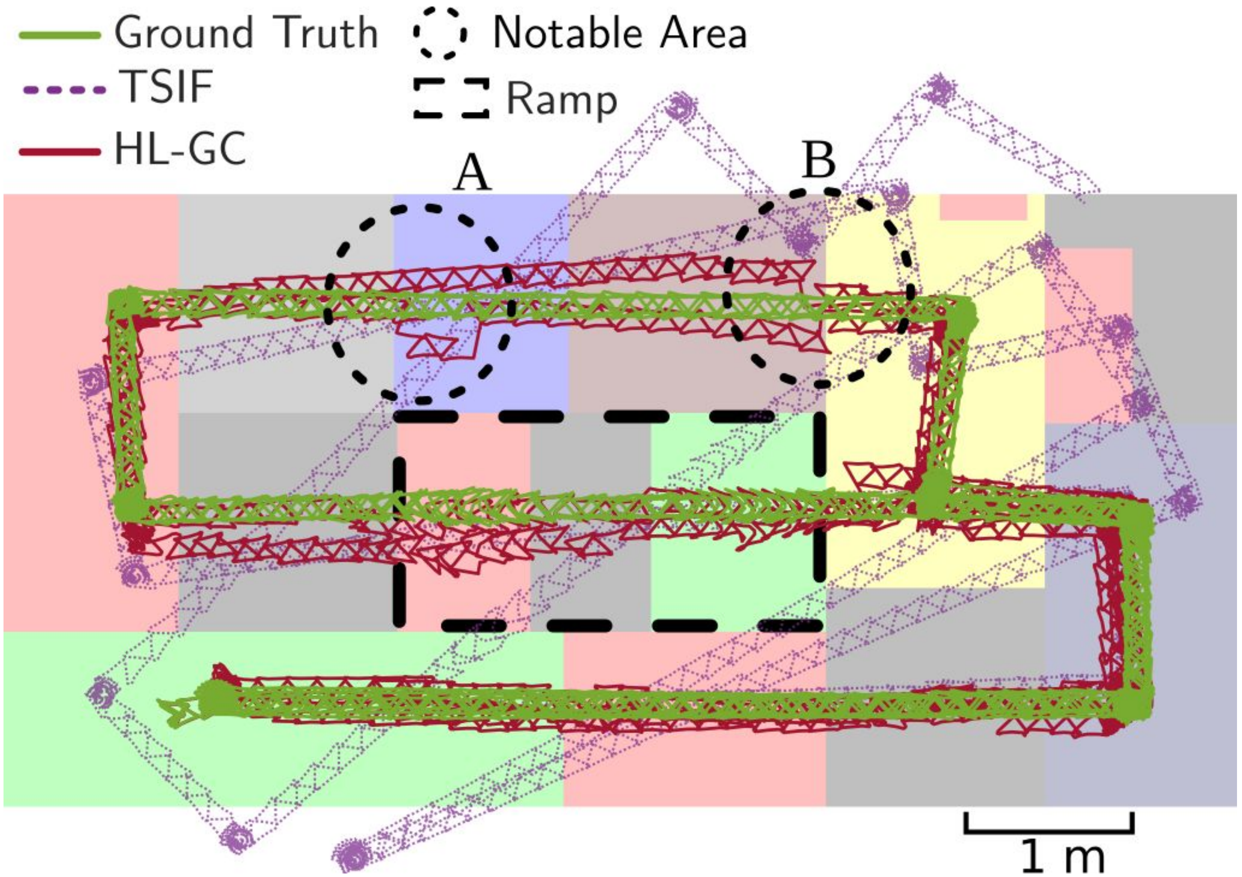
Supervised terrain classification

- Large network with GRU modules.
- Improving state-of-the-art classification results on a well-established datasets.
- Providing terrain class based on a taken step.
- Too complex for real-time inference and deployment.



Results with supervised terrain classification

- A: height information corrects estimated pose as we are not on a ramp.
- B: terrain classification helps when crossing a terrain.



Results with supervised terrain classification

- Height and terrain class information are complementary for localization.
- Using only terrain information leads to an unbounded drift in the elevation.
- Network inference is too slow.
- Initial requirements (dense 3D map) need to be more relaxed.

Mean Absolute Translation Error (ATE)						
Trial	Dist. [m]	Time [s]	TSIF [m]	HL-G [m]	HL-C [m]	HL-GC [m]
1	191	1114	0.64	0.23	0.63	**0.14**
2	331	1850	1.28	0.25	0.73	**0.11**
3	193	1090	0.72	0.21	0.61	**0.18**

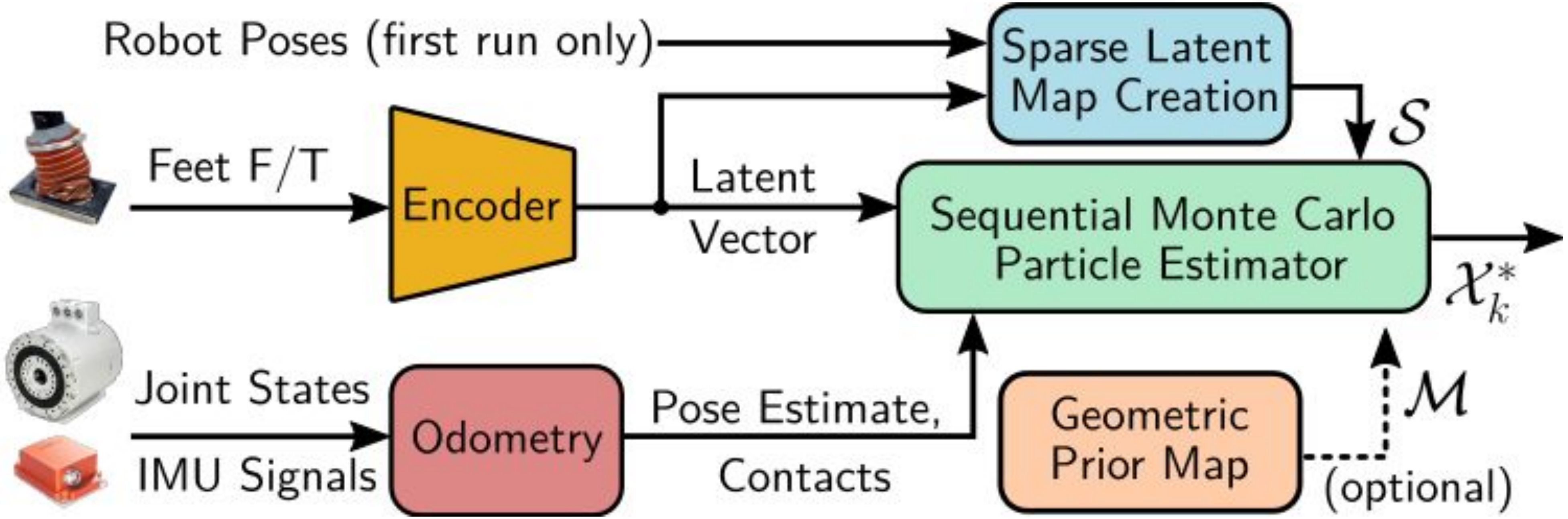
TSIF: odometry

HL-G: 2.5D dense height map

HL-C: terrain classification

HL-GC: 2.5D dense height map + terrain classification

Unsupervised haptic representation

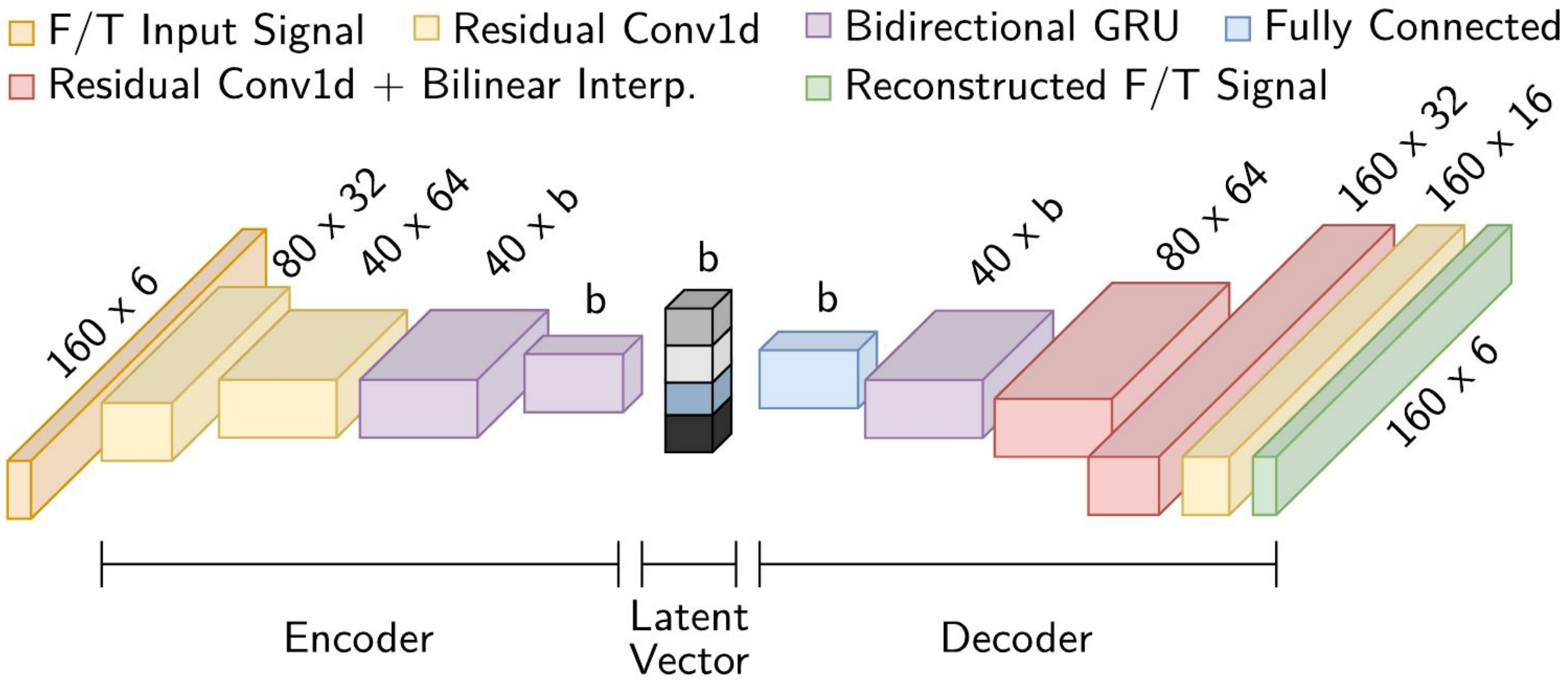


Requirements:

- Dense 2.5D height map ~~with terrain class annotations.~~
- Initial walk to gather haptic responses with known localization.

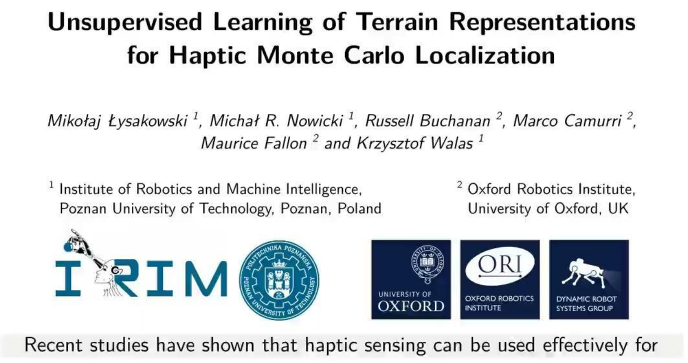
M. Łysakowski, M. R. Nowicki, R. Buchanan, M. Camurri, M. Fallon, and K. Walas, Unsupervised learning of terrain representations for haptic monte carlo localization, Int. Conference on Robotics and Automation (ICRA), p. 4642-4648, 2022.

Haptic AutoEncoder (HAE) architecture



Sparse latent map

- Gather haptic signals (no terrain classification) during the first run.
- Train HAE that generates unsupervised haptic representation on data from the first run.
- We create a sparse map of haptic representations for localization runs.



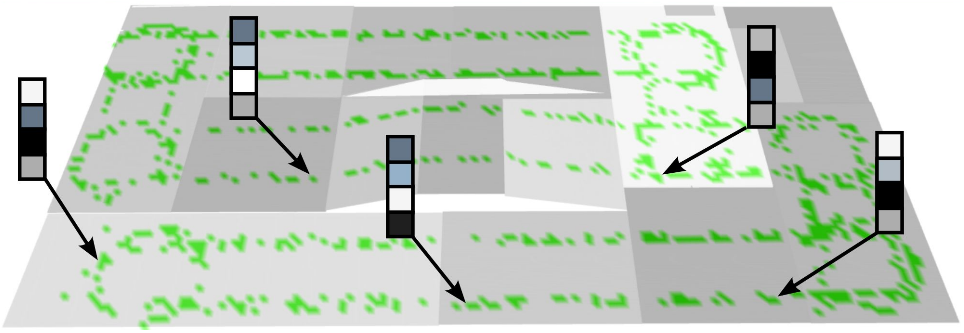
Unsupervised Learning of Terrain Representations for Haptic Monte Carlo Localization

Mikołaj Łysakowski [1], Michał R. Nowicki [1], Russell Buchanan [2], Marco Camurri [2], Maurice Fallon [2] and Krzysztof Walas [1]

[1] Institute of Robotics and Machine Intelligence, Poznan University of Technology, Poznan, Poland

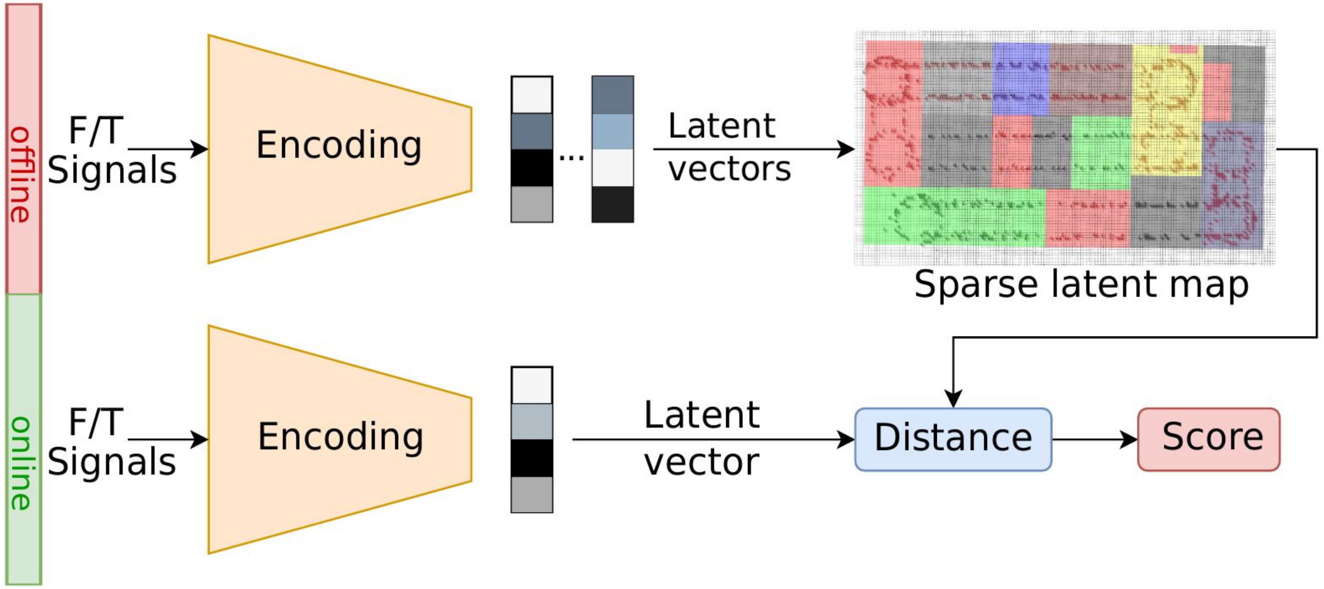
[2] Oxford Robotics Institute, University of Oxford, UK

Recent studies have shown that haptic sensing can be used effectively for



Localization phase with sparse latent map

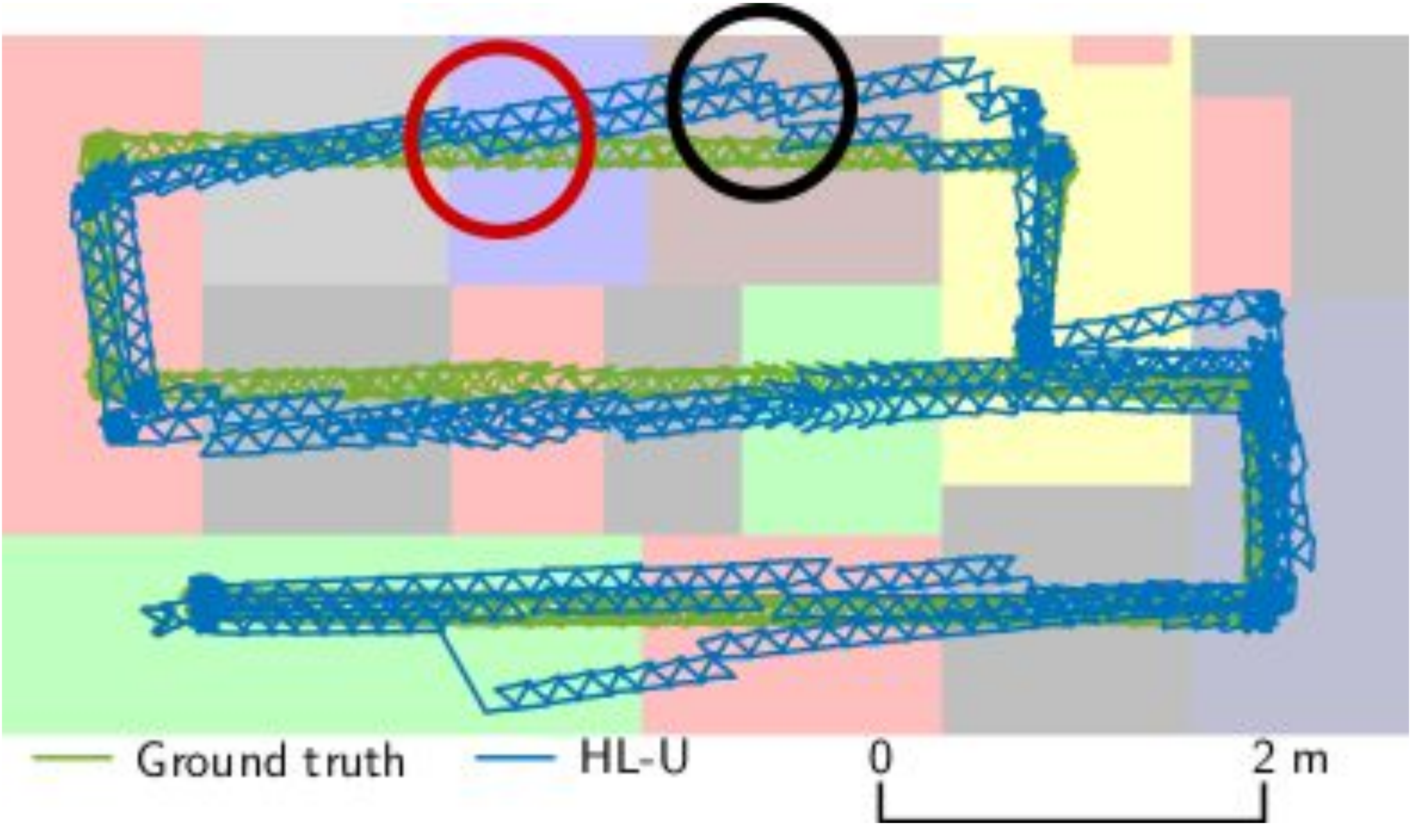
- The initial haptic response is encoded into latent vectors.
- The latent vector is compared to the closest entry in the latent map.
- We adjust particle weights based on distances in latent representations.



Results for unsupervised haptic representation

The corrections for robot localization for HL-U occur:

- once a robot crosses to a different terrain class (red circle),
- during localization over the same terrain type (black circle).



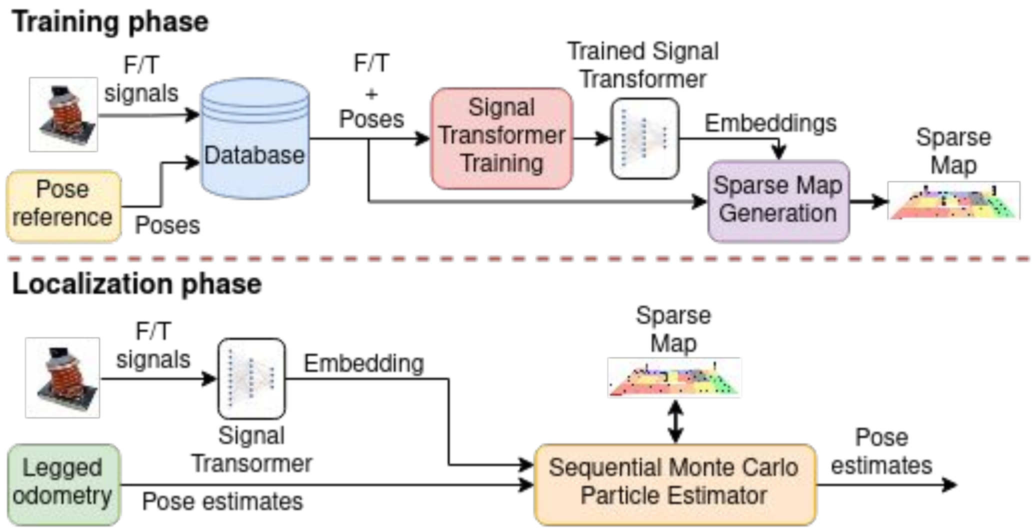
Results for unsupervised haptic representation (HL-GU and HL-U)

- The unsupervised latent representation is also complementary to the height information.
- The unsupervised latent representation (HL-U) outperforms terrain classification (HL-C) for localization when no geometry is used.
- Dense 2.5D terrain geometry is still needed to provide sufficient accuracy.

Absolute Pose Error (APE) μ[m]				
Trial	**TSIF** [19], [4]	**HL-G** [4]	**HL-GC** [4]	**HL-GU**
1	0.64	0.23	**0.14**	0.15
2	1.28	0.25	**0.11**	0.18
3	0.72	0.21	0.18	**0.13**

Absolute Pose Error (APE) μ[m]			
Trial	**TSIF** [19], [4]	**HL-C** [4]	**HL-U**
1	0.64	0.63	**0.47**
2	1.28	0.73	**0.57**
3	0.72	0.61	**0.5**

Trained terrain representation for localization



- Let’s train representation for localization!
- Network architecture based on HAPTR

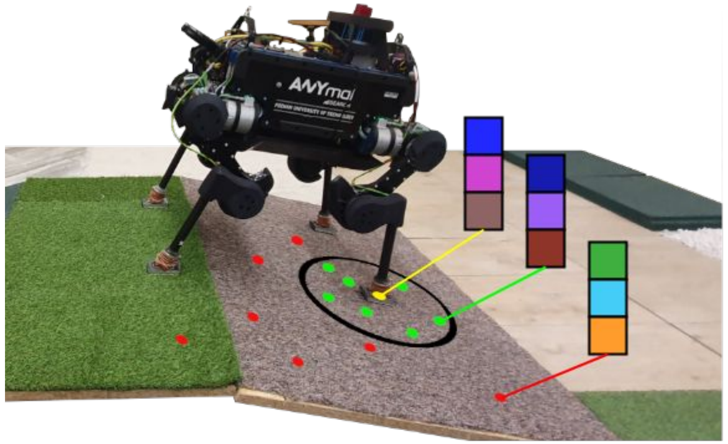
Requirements:

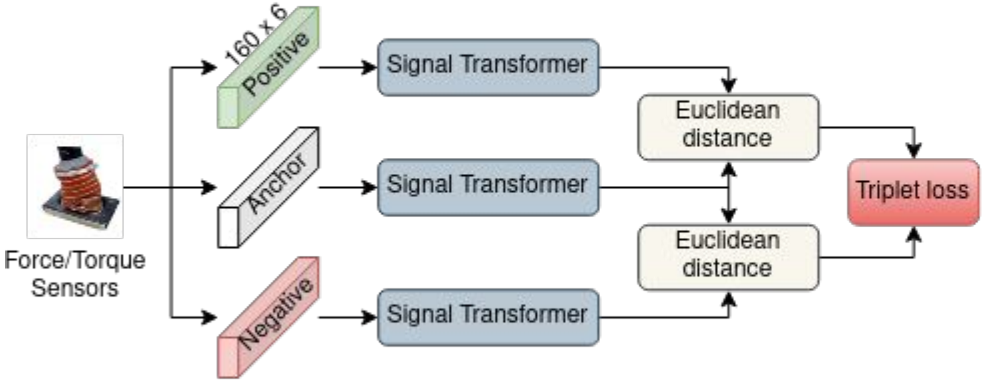
- ~~dense 2.5D height map with terrain class annotations~~
- initial walk to gather haptic responses with known localization.

D. Sójka, M. R. Nowicki, and P. Skrzypczyński, Learning an Efficient Terrain Representation for Haptic Localization of a Legged Robot, Int. Conference on Robotics and Automation (ICRA), 2023

Trained terrain representation for localization

- We assume that haptic response should be similar in some vicinity.
- We train representation based on the Euclidean position of the feet.
- Triplet loss is commonly used for large-scale place recognition.





Results for trained terrain representation (HL-T and HL-GT)

Trained representation outperforms terrain classification and unsupervised representation when:

- not using height information,
- using height information.

Trial	TSIF [24] t_{2D}	HL-C [4] t_{2D}	HL-U [18] t_{2D}	HL-T t_{2D}
1	0.34	0.39	0.17	**0.07**
2	0.92	0.22	0.14	**0.06**
3	0.51	0.29	0.18	**0.08**

Trial	HL-G [4]		HL-GC [4]		HL-GU [18]		HL-GT	
	t_{3D}	t_{2D}	t_{3D}	t_{2D}	t_{3D}	t_{2D}	t_{3D}	t_{2D}
1	0.23	0.23	0.14	0.12	0.15	0.09	**0.09**	**0.08**
2	0.25	0.20	**0.11**	0.11	0.18	0.12	**0.11**	**0.10**
3	0.21	0.18	0.18	0.17	0.13	0.13	**0.09**	**0.09**

Results for trained terrain representation (HL-T and HL-GT)

- Without a height map, we still get an elevation drift.
- Having a dense 2.5D height map generates the best results.
- We can use a sparse height map build during an initial walk (HL-ST) to get almost the best results with a more practical approach (a single staging run without dense map building)

Trial	HL-T		HL-GT		HL-ST	
	t_{3D}	t_{2D}	t_{3D}	t_{2D}	t_{3D}	t_{2D}
1	0.51	**0.07**	**0.09**	0.08	**0.09**	0.09
2	0.77	**0.06**	**0.11**	0.10	**0.11**	0.11
3	0.44	**0.08**	**0.09**	0.09	0.10	0.09

Conclusions

- Localizing the walking robot based on terrain description is possible and can be used in case of vision/LiDAR failure.
- Supervised, unsupervised and trained representation approaches can be used with classical solutions (i.e. particle filter) to improve localization performance.
- There are still many limitations - we need better datasets to show robustness, performance on unseen data, go outdoors, and further push what is feasible without cameras/LiDARs.

Special thanks to: Jakub Bednarek, Michał Bednarek, Mikołaj Łysakowski, Krzysztof Walas, Dominik Belter, Piotr Skrzypczyński, Damin Sójka and our collaborators from ETH Zurich, University of Oxford, University of Edinburgh, University of Pisa, ANYbotics, qb robotics, KGHM CURPUM

subTerranean Haptic INvestiGator – THING
H2020-ICT-2017-1 Grant agreement ID: 780883

THING

[WIP] Unitree with force-torque sensors

- ANYmal reached the end of life in our case, while a new one is quite expensive.
- We moved on to Unitree robots that were retrofitted with force-torque sensors, GNSS RTK, and Xsens AHRS.
- We plan on going outdoors with haptic localization.

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