Haptic Monte Carlo Localisation for a Legged Robot

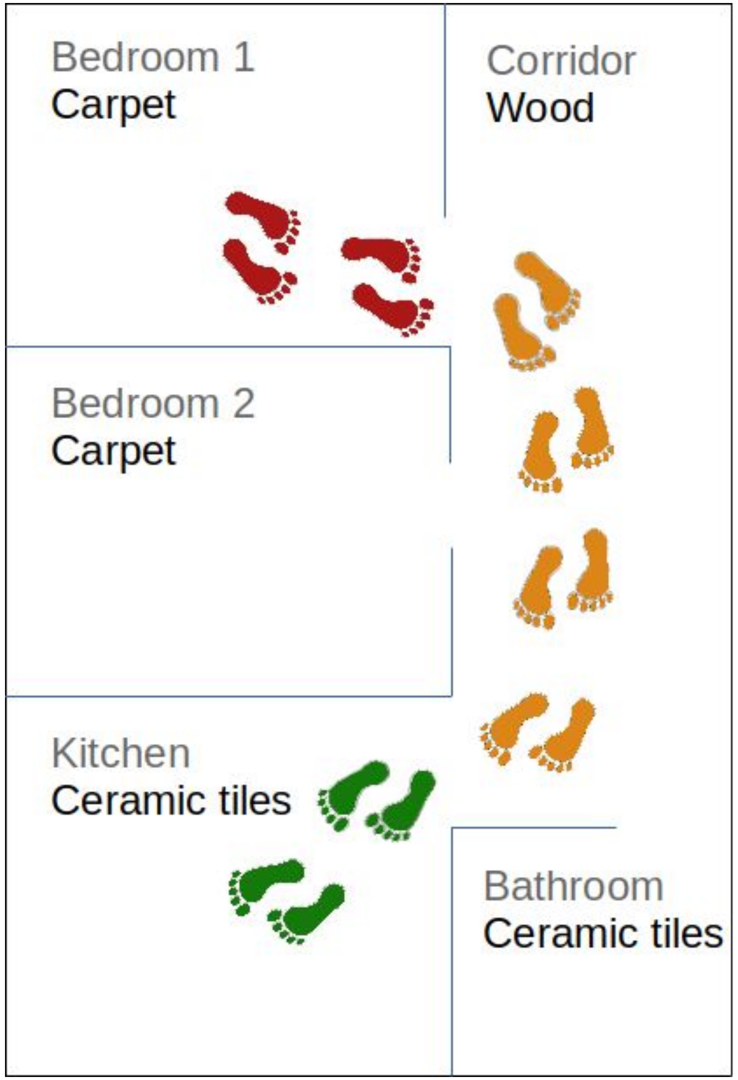
Michał Nowicki, PhD

About me

- PhD at Poznan University of Technology (2018)
- 3-month research internship at the University of Saragossa on visual SLAM
- 3-month research stay at FZI in Germany on the behaviors of legged robots
- PI in 3 projects at PUT:
  - Autonomous robot to deliver packages in a park (as a student)
  - Graph optimization for smartphone-based localization
  - AGV utilizing 3D LiDARs and 3D maps
- Leading autonomy for an autonomous indoor drone for the Polish military (WZL2) (2017-2019)
- Leading perception in camera-based ADAS system for Solaris Bus & Coach (2018-2021)
- PostDoc in THING project on subterranean legged locomotion, EU Horizon 2020 (2020-2021)
- Head of Autonomy/Autonomy Lead for ~1000 last-mile delivery mobile robots at COCO, USA (2021-2023)
- Head of Autonomy for autonomous outdoor mobile vehicle for Samsung in Wronki @ PI (2023)
- Localization Lead for underwater drones for inspection at Hydromea, Switzerland (started 10.2023)

Night mission to the kitchen

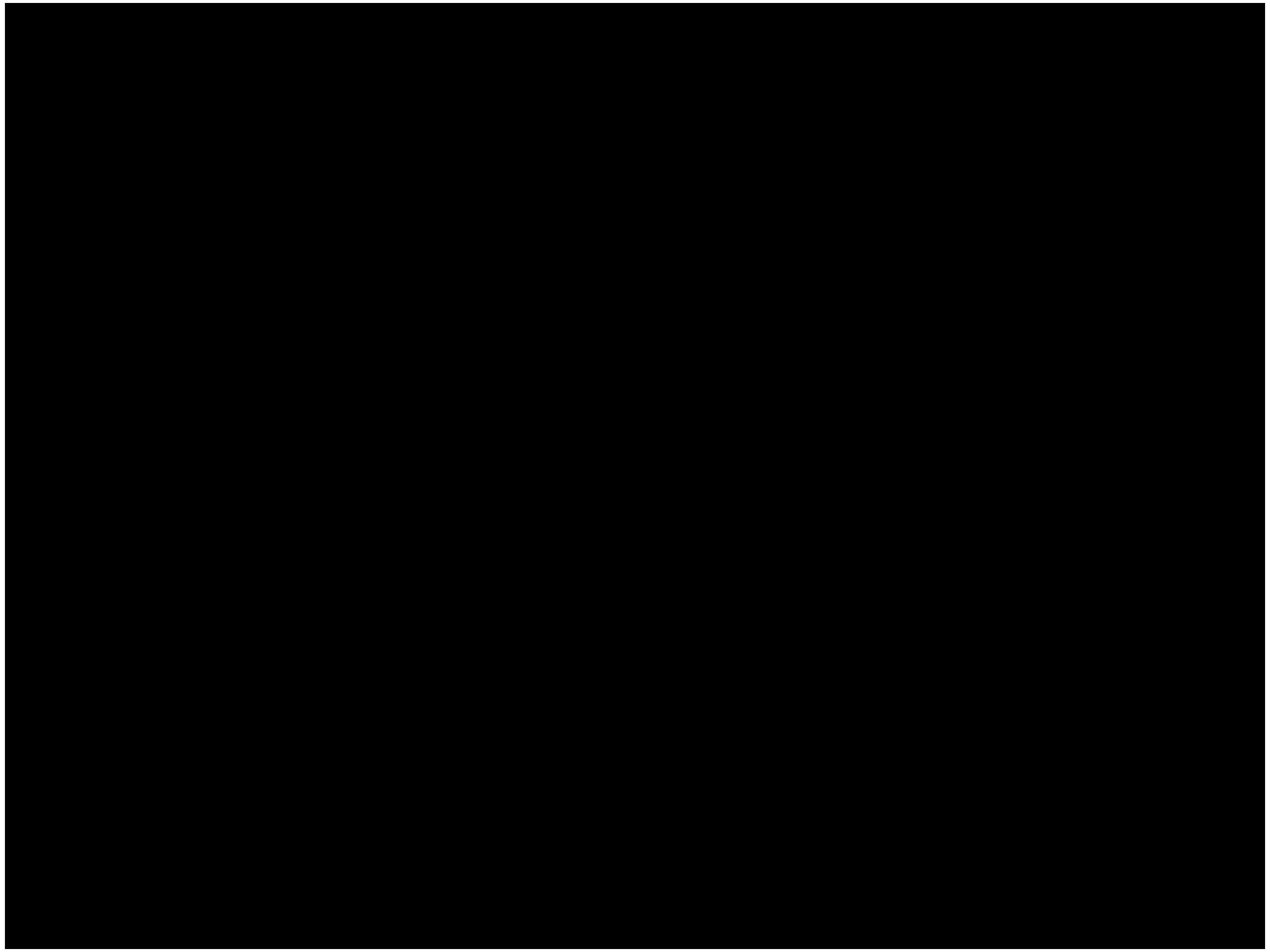
- You wake up in the middle of the night
- You need to get some water from the kitchen
- You know the map of your flat
- You don’t want to turn on the light not to wake others up
- You are walking barefoot, so you can sense the materials on the floor



Industrial application

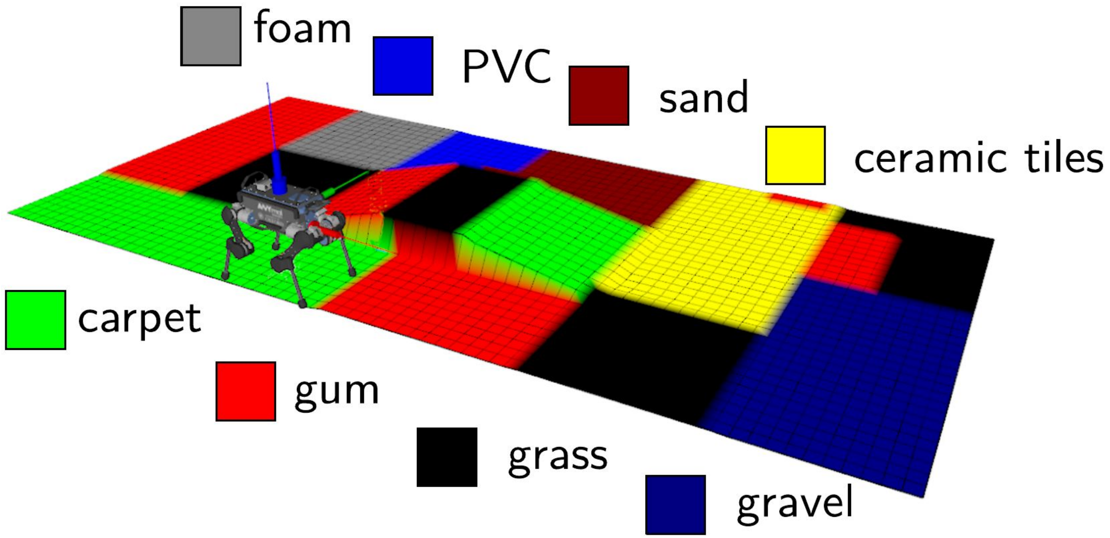
- Repeatable inspections in hot, humid, challenging environments where it is better to send a robot than a person
- In these conditions, vision/LiDARs might fail
- We need additional robustness to be able to deploy it

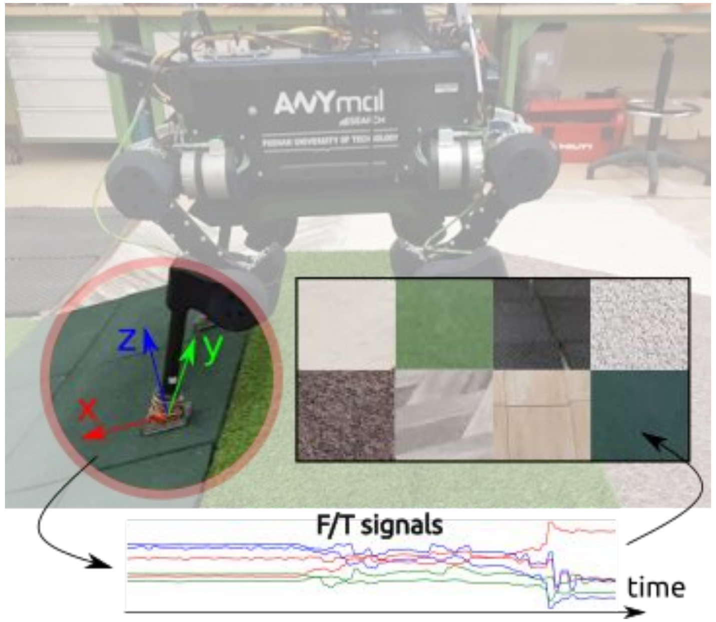
Industrial application



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)

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

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IRIM

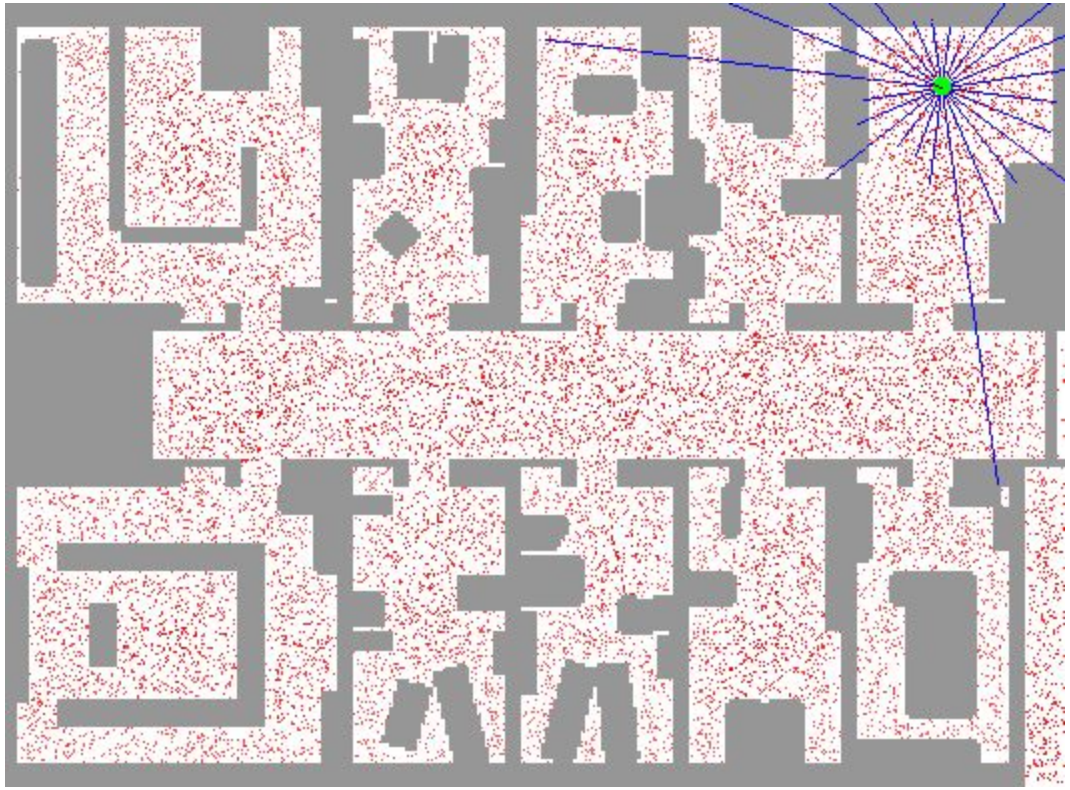
UNIVERSITY OF OXFORD

ORI OXFORD ROBOTICS INSTITUTE

DYNAMIC ROBOT SYSTEMS GROUP

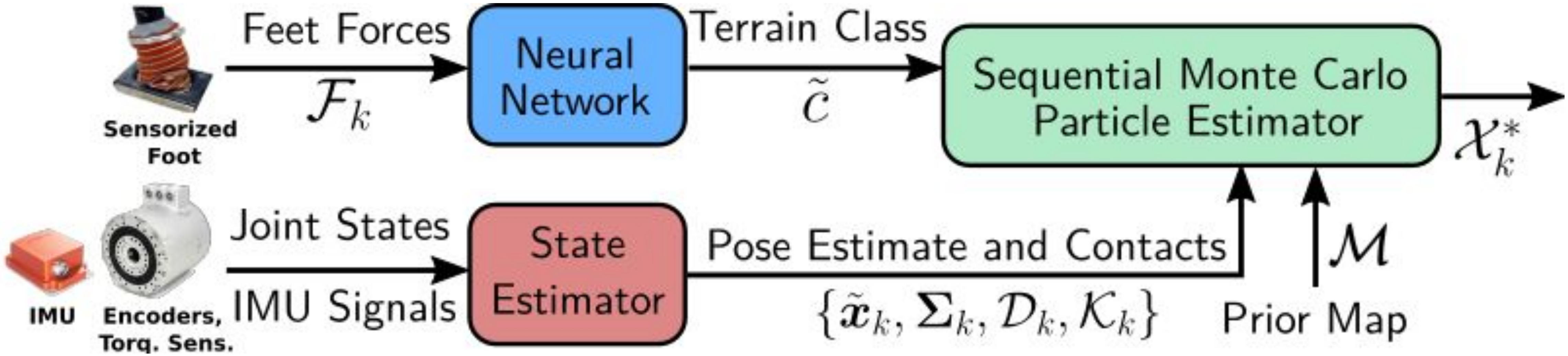
Recent studies have shown that haptic sensing can be used effectively for

Sequential Monte Carlo Particle Estimator



graphics from : https://commons.wikimedia.org/wiki/File:Particle_filters.gif Eleschinski2000, CC BY-SA 4.0, via Wikimedia Commons

Localization with Terrain Classification



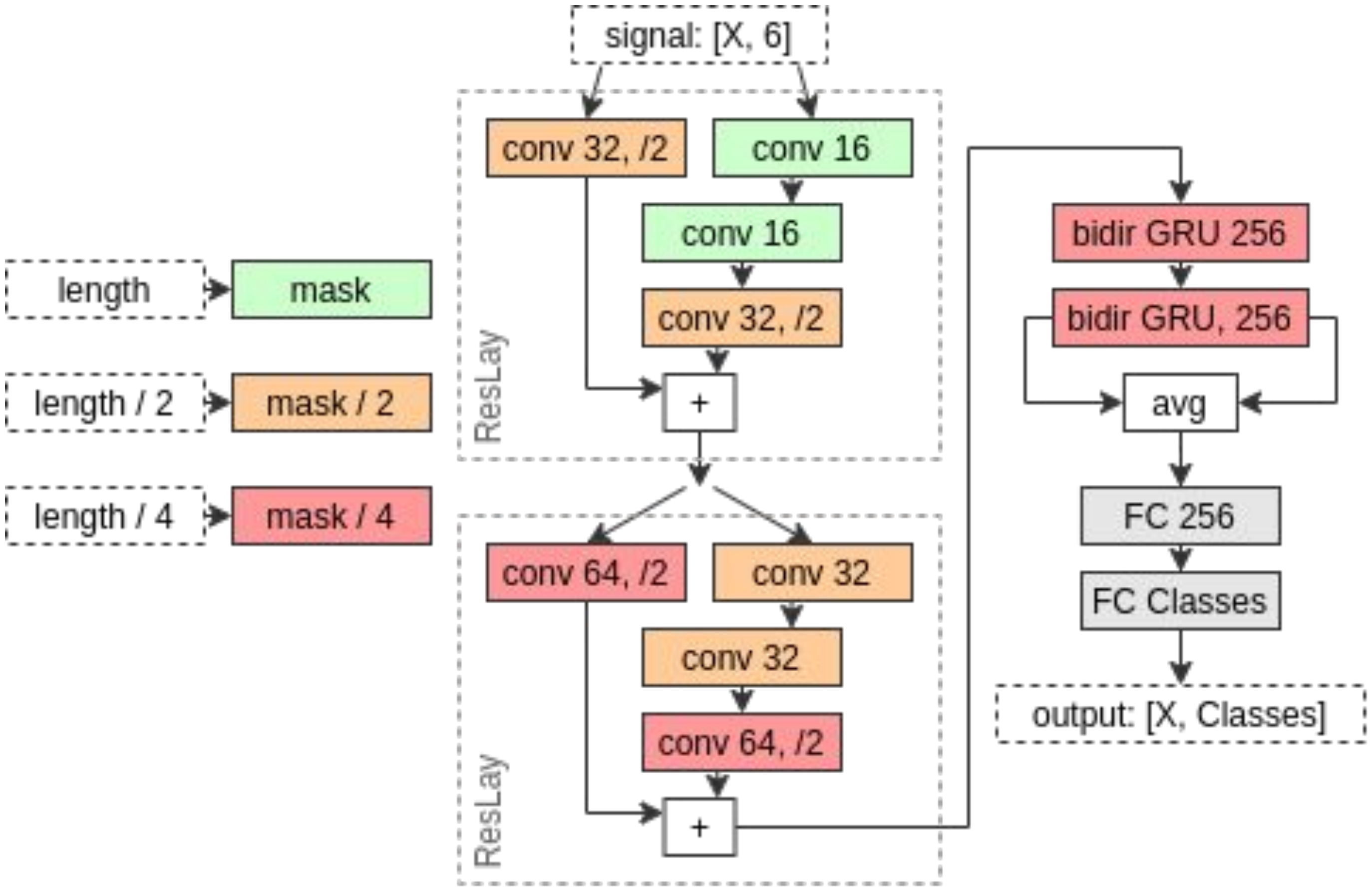
Requirements:

- 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

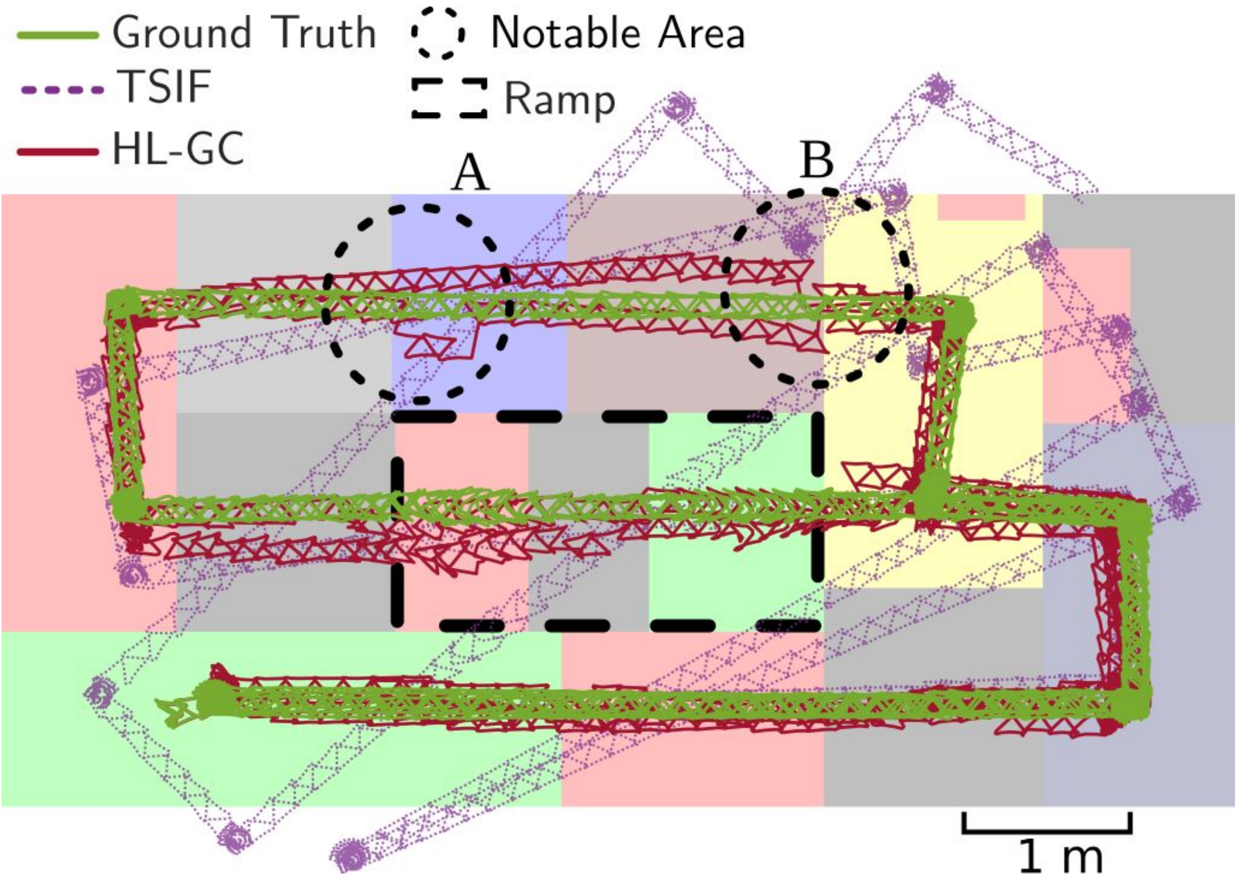
Supervised learning approach

- large network with GRU modules
- improving state-of-the-art on a well-established datasets
- providing terrain class based on a taken step
- too complex for real-time inference and deployment



Results

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

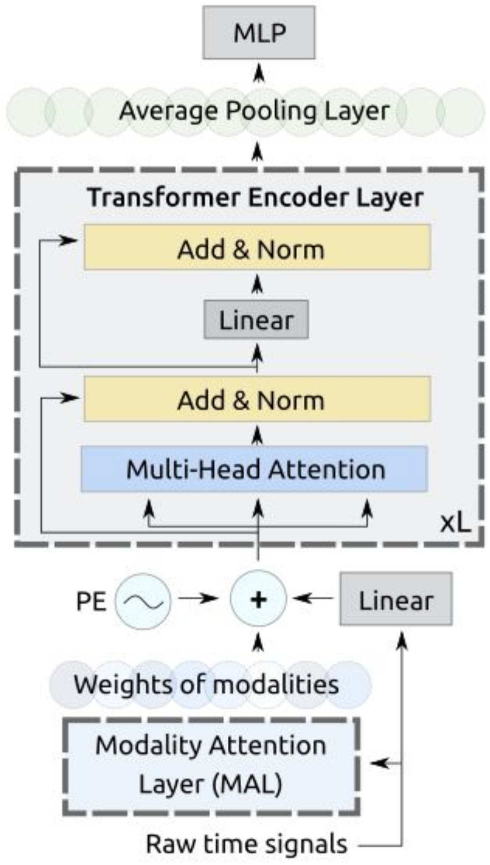


Results

- 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**

Haptic transformer for terrain representation

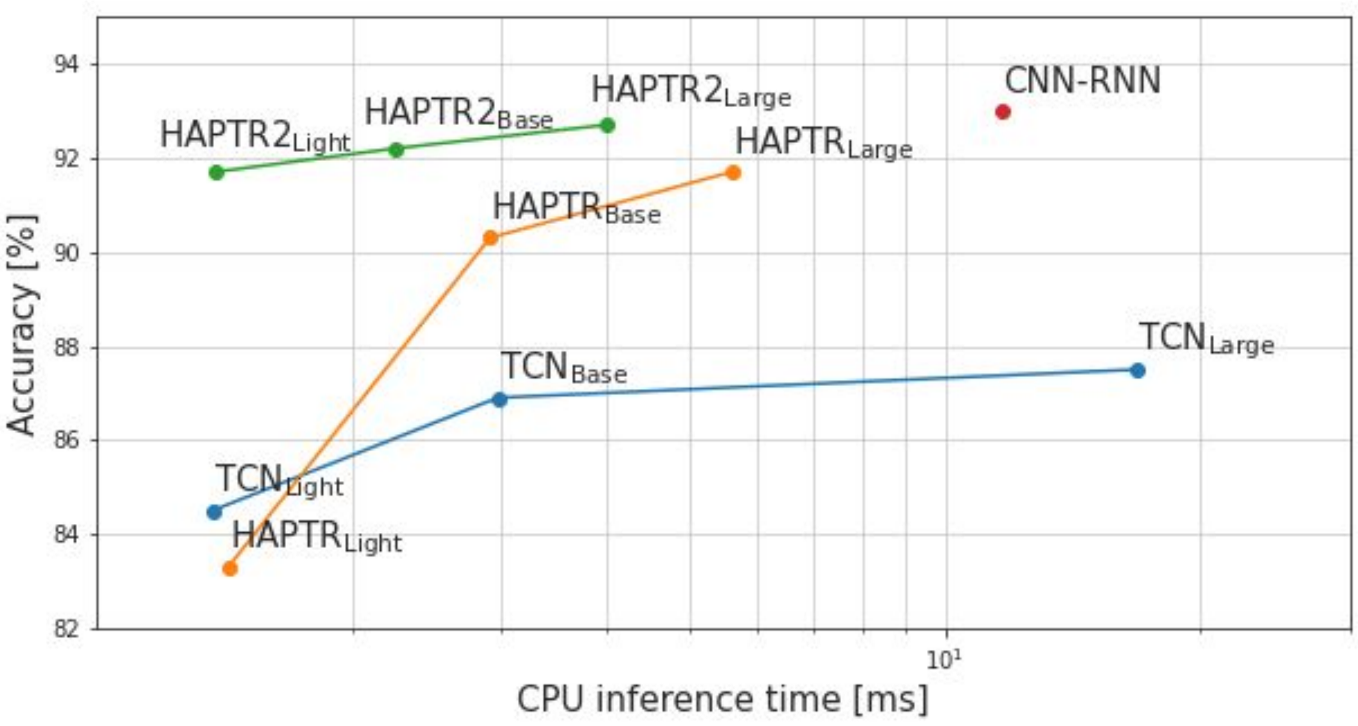


- Existing terrain classification networks focused on improving the accuracy on the dataset while being too large to be used on a robot.
- We decided to optimize efficiency.
- We based our approach on Transformer.
- We add the MAL layer to dynamically weight force/torque to add robustness.

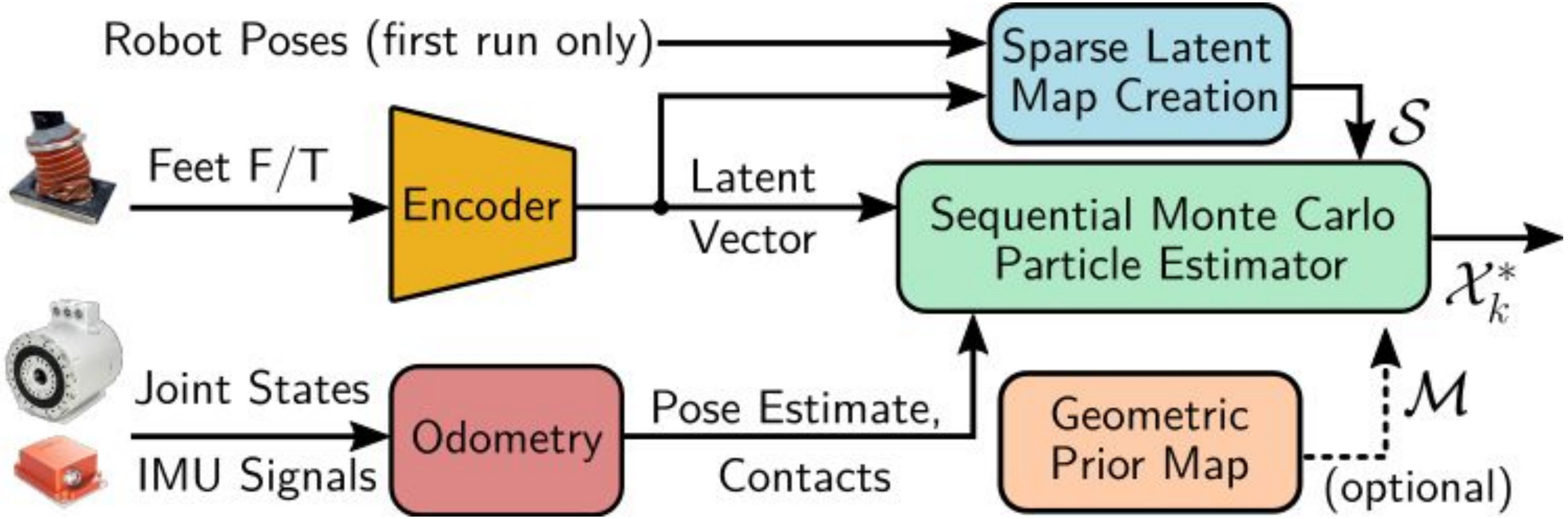
M. Bednarek, M. R. Nowicki, and K. Walas, HAPTR2: Improved Haptic Transformer for legged robots' terrain classification, Robotics and Autonomous Systems, 158, 2022.

Results

- Almost top accuracy using a fraction of resources
- Real-time operation on a robot
- Increased robustness to possible sensory issues during operation



Unsupervised haptic representation

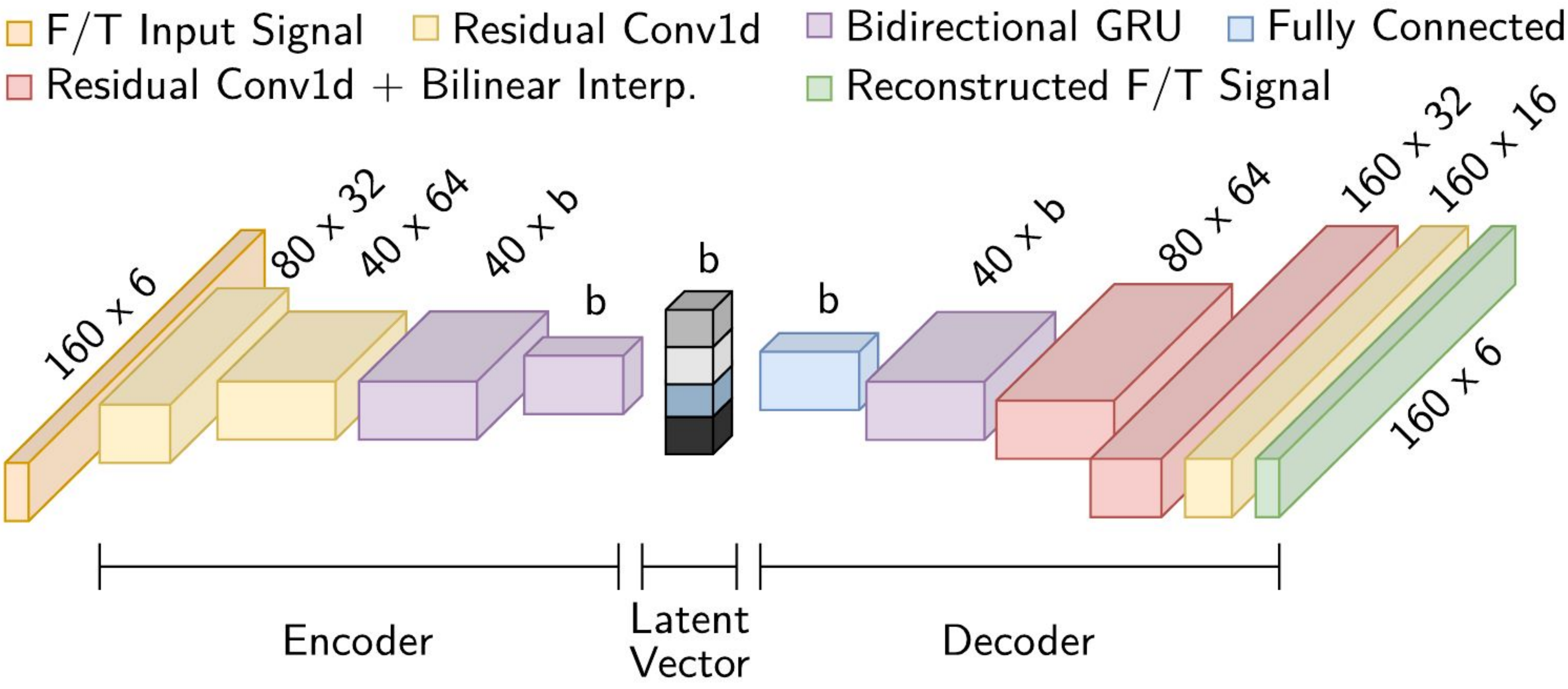


Requirements:

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

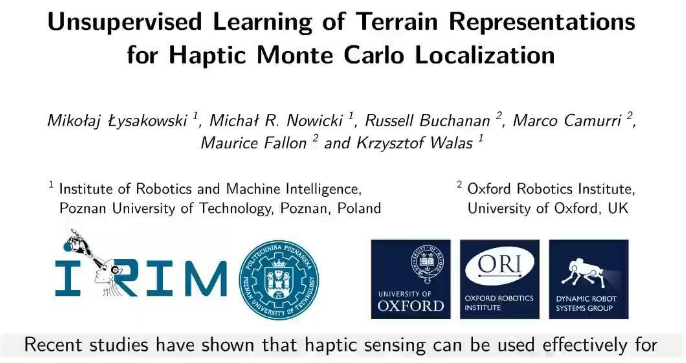
M. Łysakowski, M. R. Nowicki, R. Buchanan, M. Camurri, M. Fallon, and K. Walas, Unsupervised learning of terrain representations for haptic monte carlo localization, Int. Conference on Robotics and Automation (ICRA), p. 4642-4648, 2022.

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

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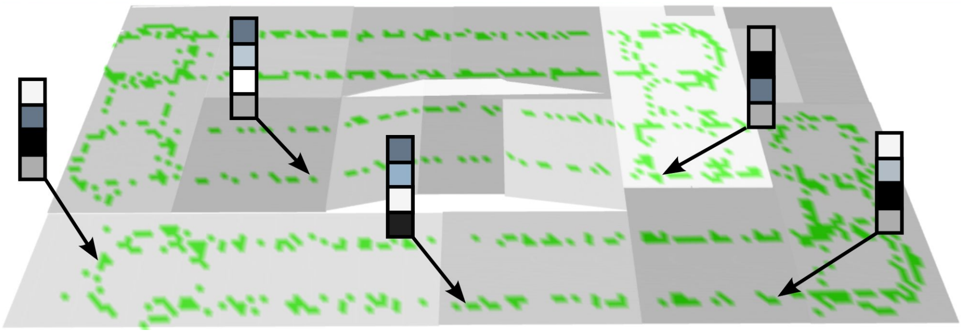
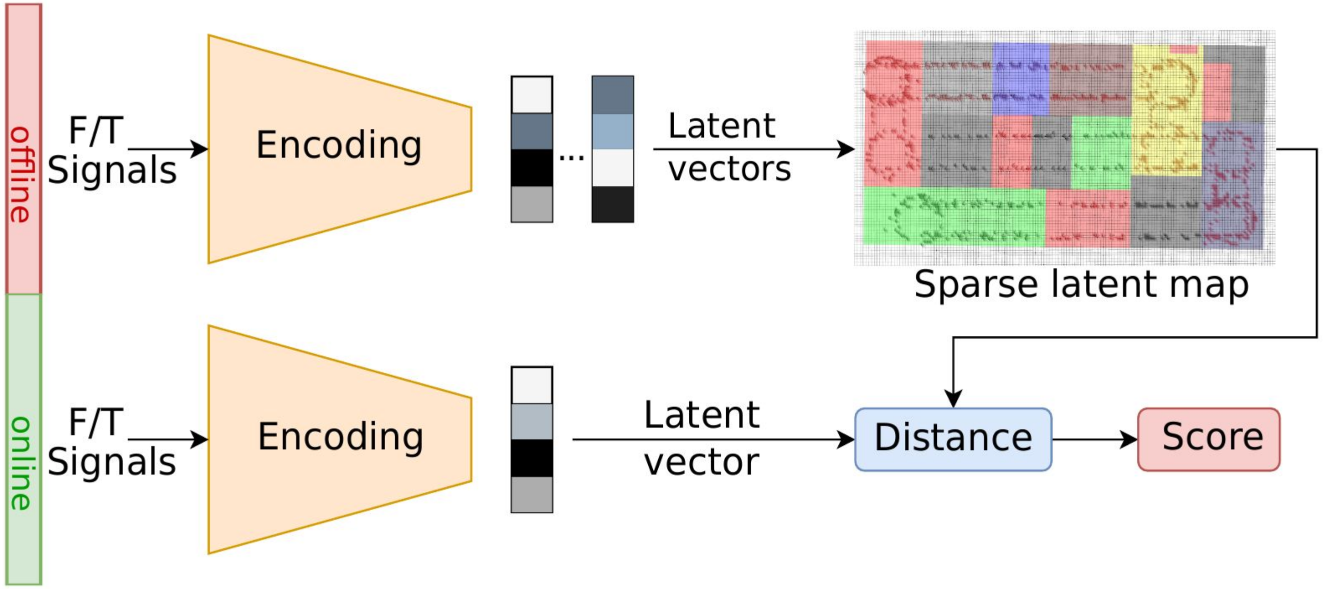
Recent studies have shown that haptic sensing can be used effectively for



Localization phase with sparse latent map

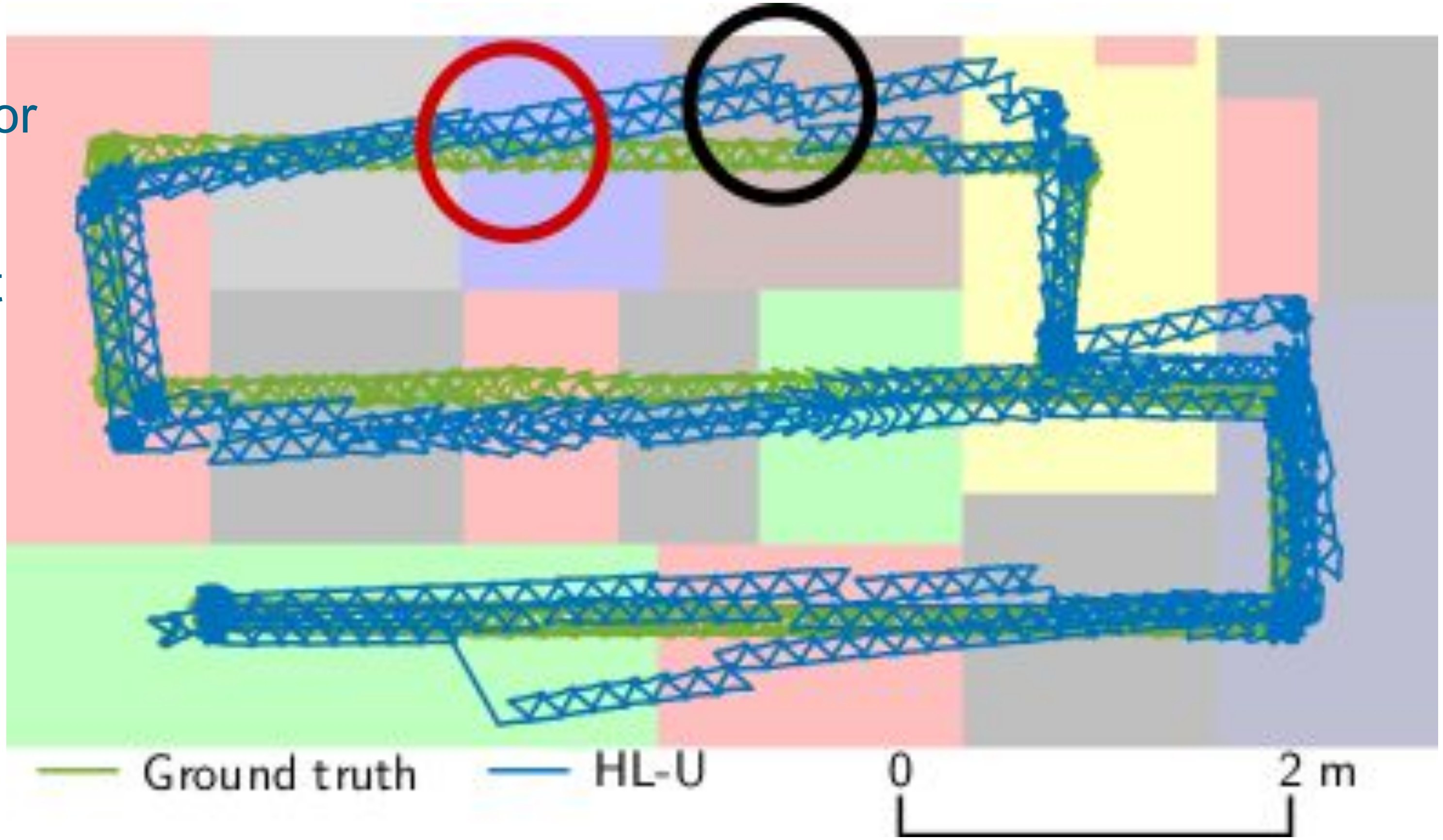
- The initial haptic response is encoded into latent vectors.
- The latent vector is compared to the closest entry in the latent map.
- We adjust particle weights based on distances in latent representations.



Results

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)



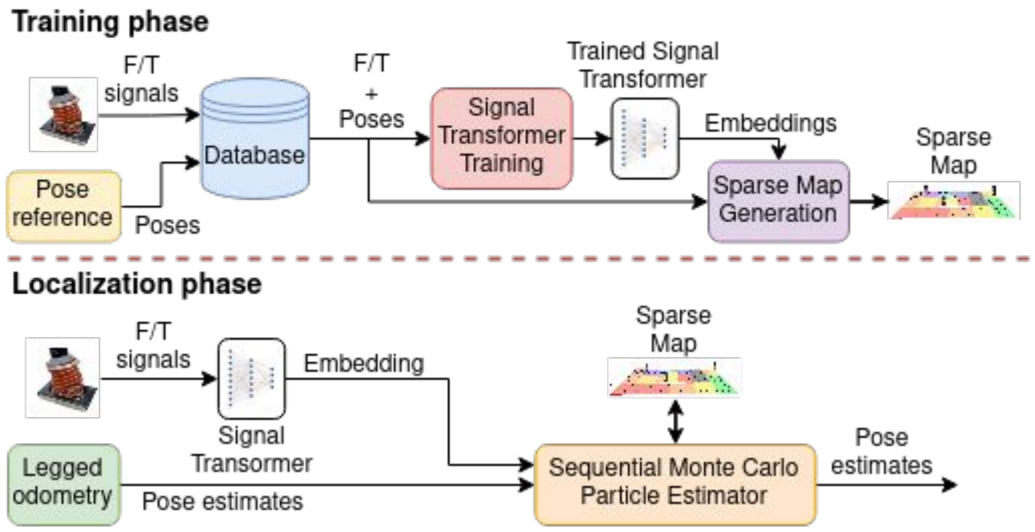
Results

- The unsupervised latent representation is also complementary to the height information
- The unsupervised latent representation outperforms terrain classification for localization when no geometry is used
- dense geometry is still need 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 representation for localization



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

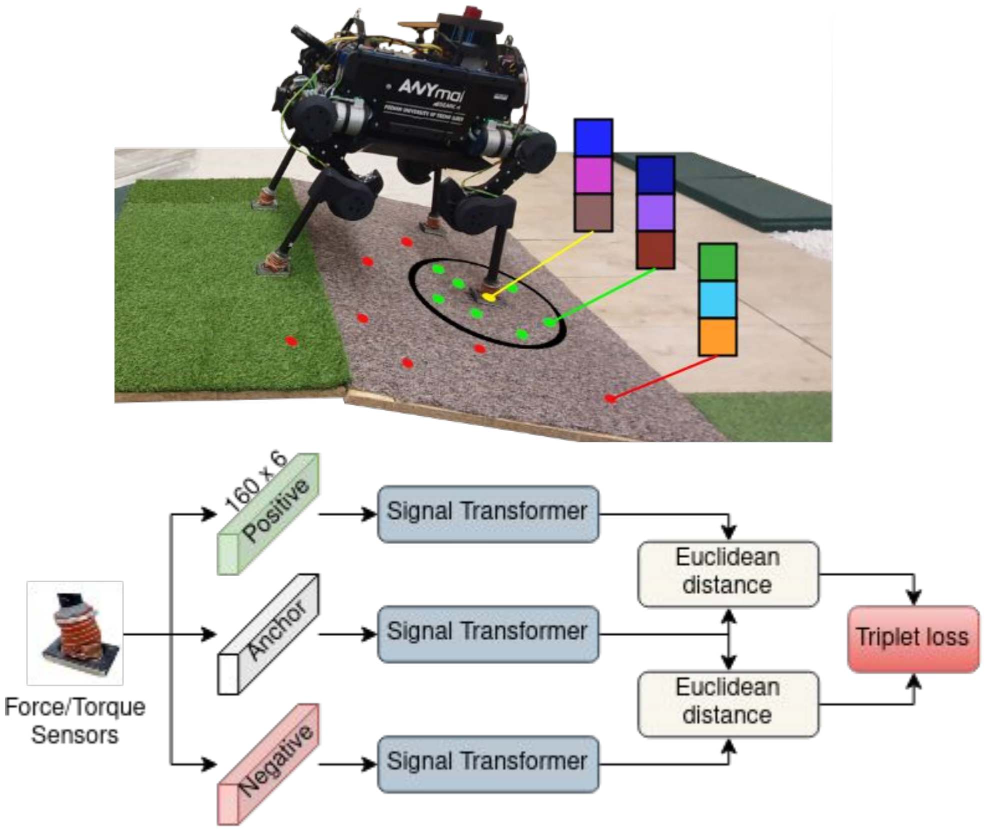
Requirements:

- ~~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 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

Trained representation outperforms terrain classification and unsupervised representation when:

- not using (top) height information.
- using (bottom) 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

- 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 to get almost the best results with a more practical approach (single staging run)

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 robot based on terrain description is possible
- Haptic transformer for efficient terrain representation
- Supervised, unsupervised, trained representation approaches

Special thanks to: Jakub Bednarek, Michał Bednarek, Mikołaj Łysakowski, Krzysztof Walas, Dominik Belter, Piotr Skrzypczyński 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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