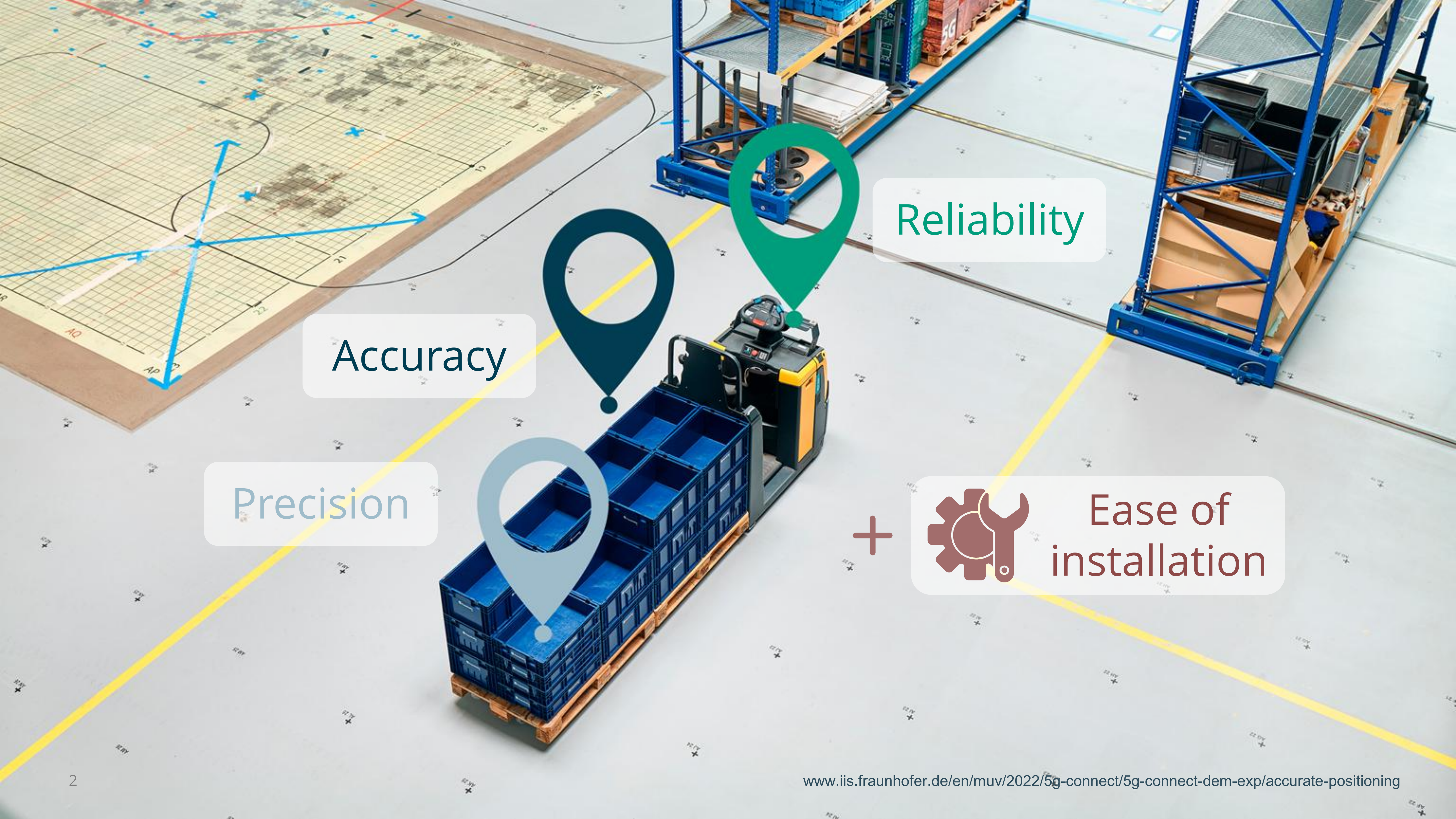
KU LEUVEN | DRAMCO

ELLIIT 2026 SEMINAR

Label-Efficient Self-Supervised Acoustic Indoor Positioning Enabling Effortless Deployment

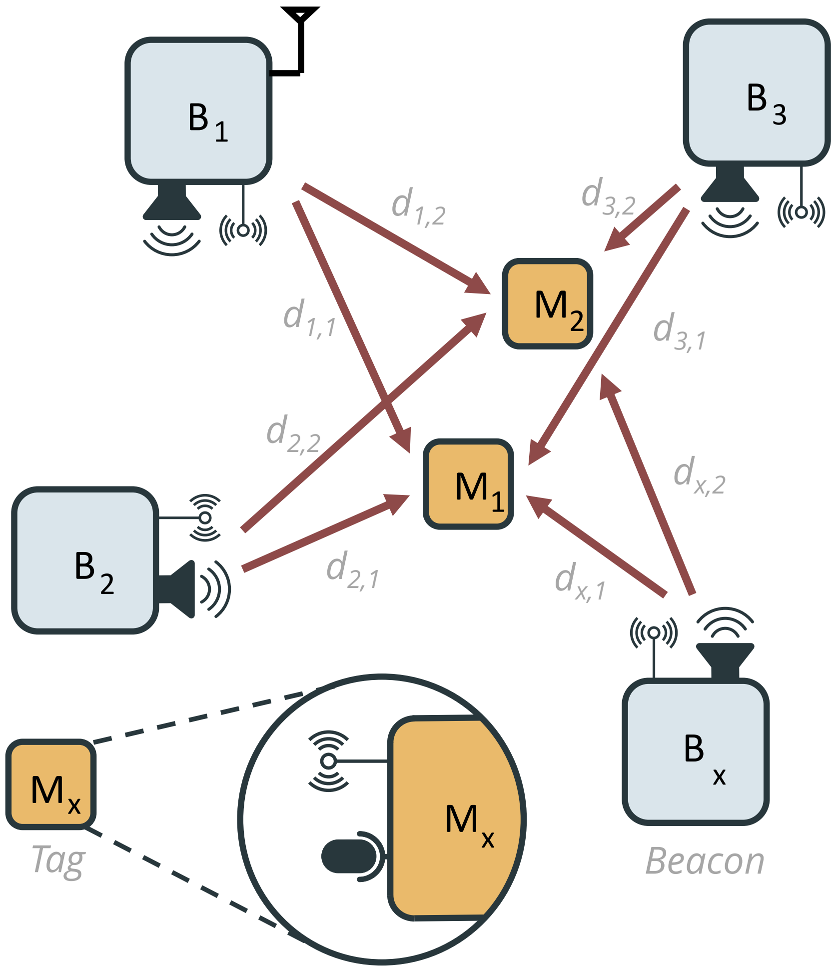
DAAN DELABIE

DRAMCO

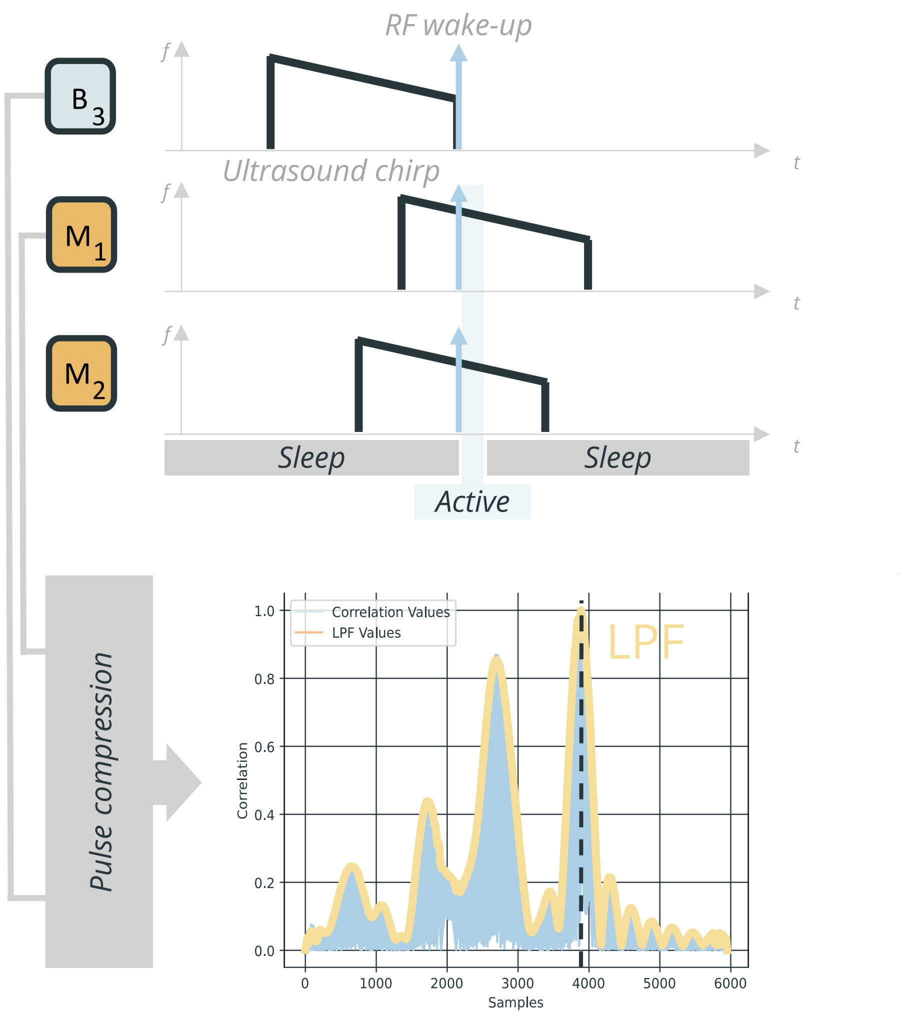


www.iis.fraunhofer.de/en/muv/2022/5g-connect/5g-connect-dem-exp/accurate-positioning

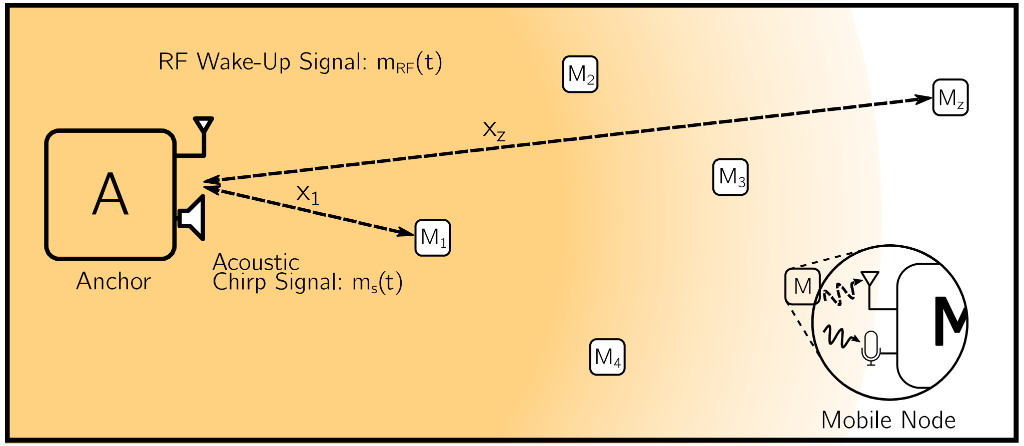
SYSTEM OVERVIEW

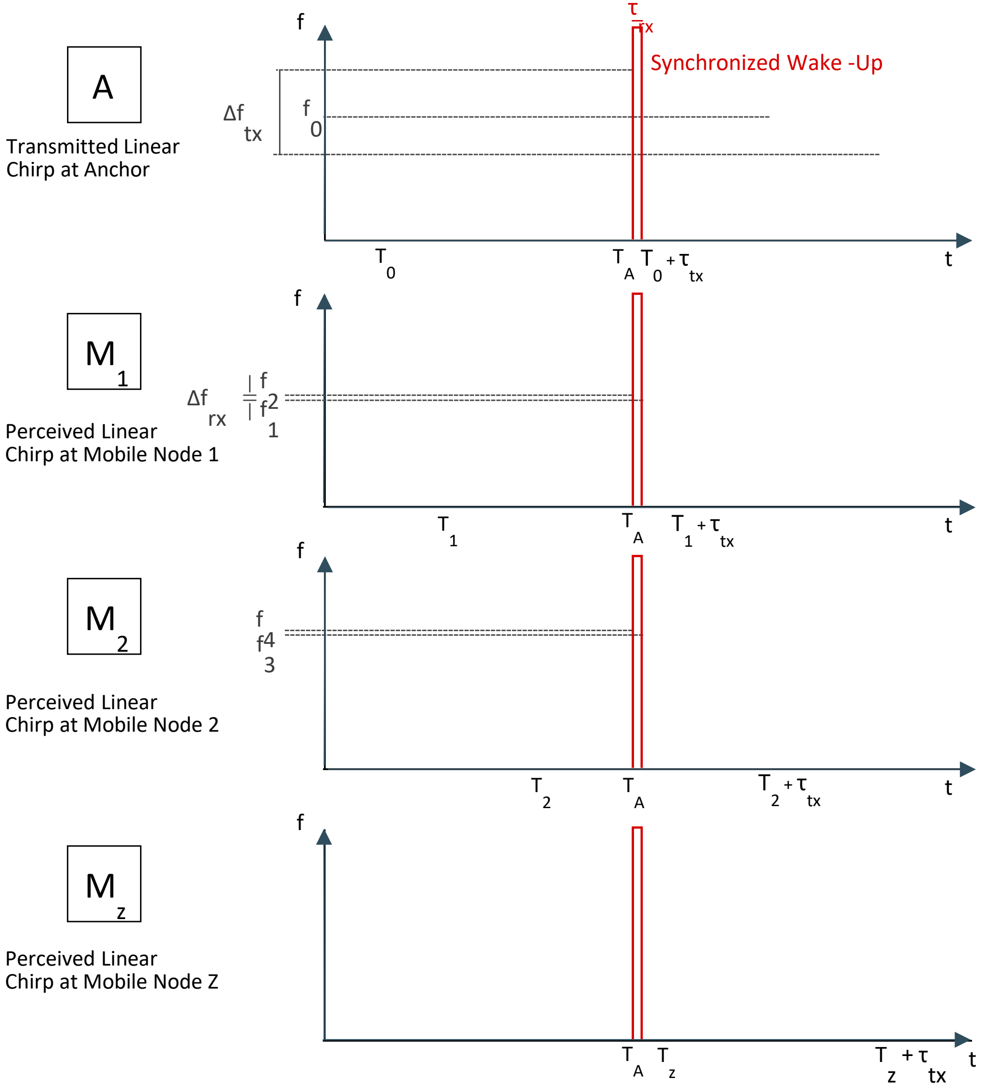


SIGNALLING



Published


RF Wake-Up Signal: m_RF(t)
A
Anchor
Acoustic
Chirp Signal: m_s(t)
x_Z
x_1
M_1
M_2
M_3
M_4
M_z
M
M
Mobile Node


A
Transmitted Linear
Chirp at Anchor
f
Δf
tx
f
0
τ
tx
Synchronized Wake -Up
T
0
T
A
T
0
+ τ
tx
t
M
1
Perceived Linear
Chirp at Mobile Node 1
Δf
rx
f
2
f
1
T
1
T
A
T
1
+ τ
tx
M
2
Perceived Linear
Chirp at Mobile Node 2
f
4
f
3
T
2
T
A
T
2
+ τ
tx
M
z
Perceived Linear
Chirp at Mobile Node Z
T
A
T
z
T
z
+ τ
tx

INTRODUCTION

POSITIONING SYSTEM

POSITIONING IMPROVEMENTS

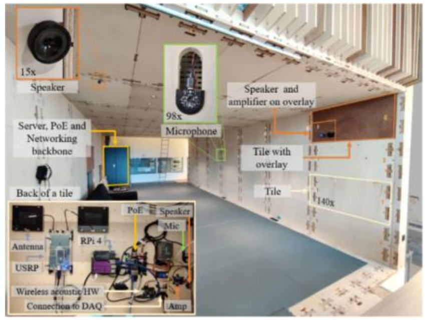
TOWARDS EASE-OF-INSTALLATION

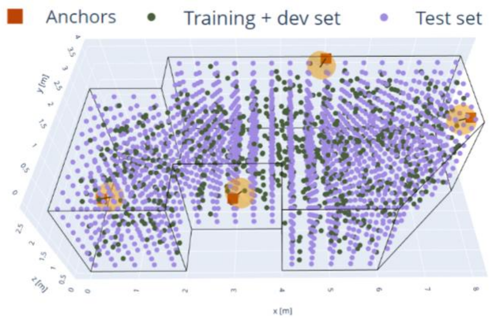
CONCLUSION

KU LEUVEN

POSITIONING IMPROVEMENT STRATEGIES

Methodologies for Experiments





Model Based

Hardware Design

Optimal Anchor Placement

Scaling Distributed Deployment

Position Dependent Anchor Selection

Data-Driven

Input Features

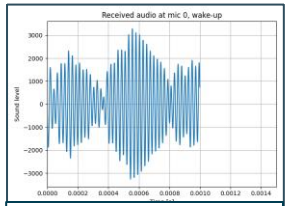
Neural Network Models

Dynamic Assessment

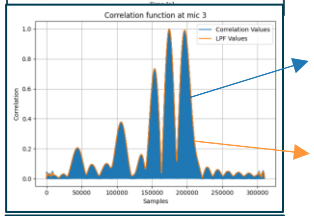
Label-Efficient Self-Supervised

DATA-DRIVEN APPROACH

Input Data

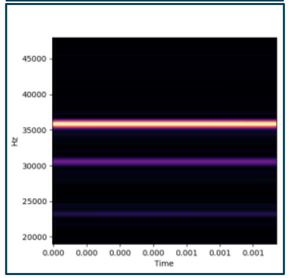


Audio

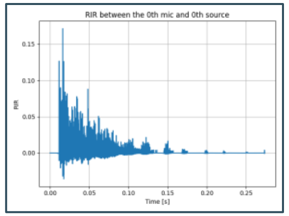


PC

LPF



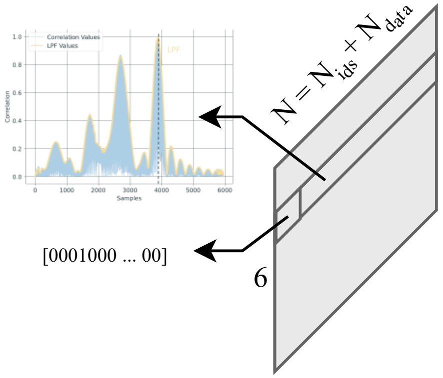
Spect.



RIR

Processed Input Data

Anchor – MN
Data values

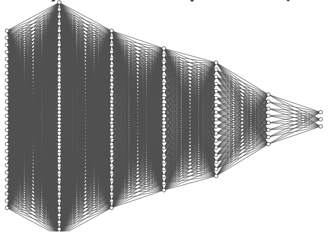


Anchor Selection
(6 anchors)
+
One-hot encoding

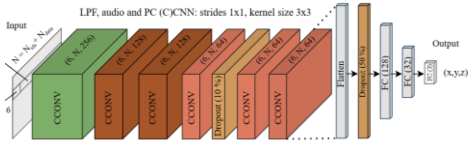
MLP: flatten
GNN: anchor nodes

Neural Network Models

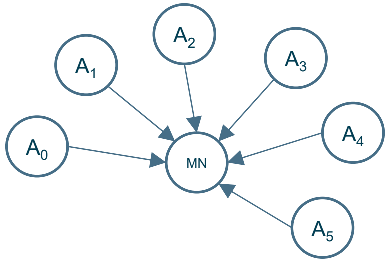
Multilayer Perceptron (MLP)



(Circular) Convolutional Neural Network ((C)CNN)



Graph Neural Network (GNN)

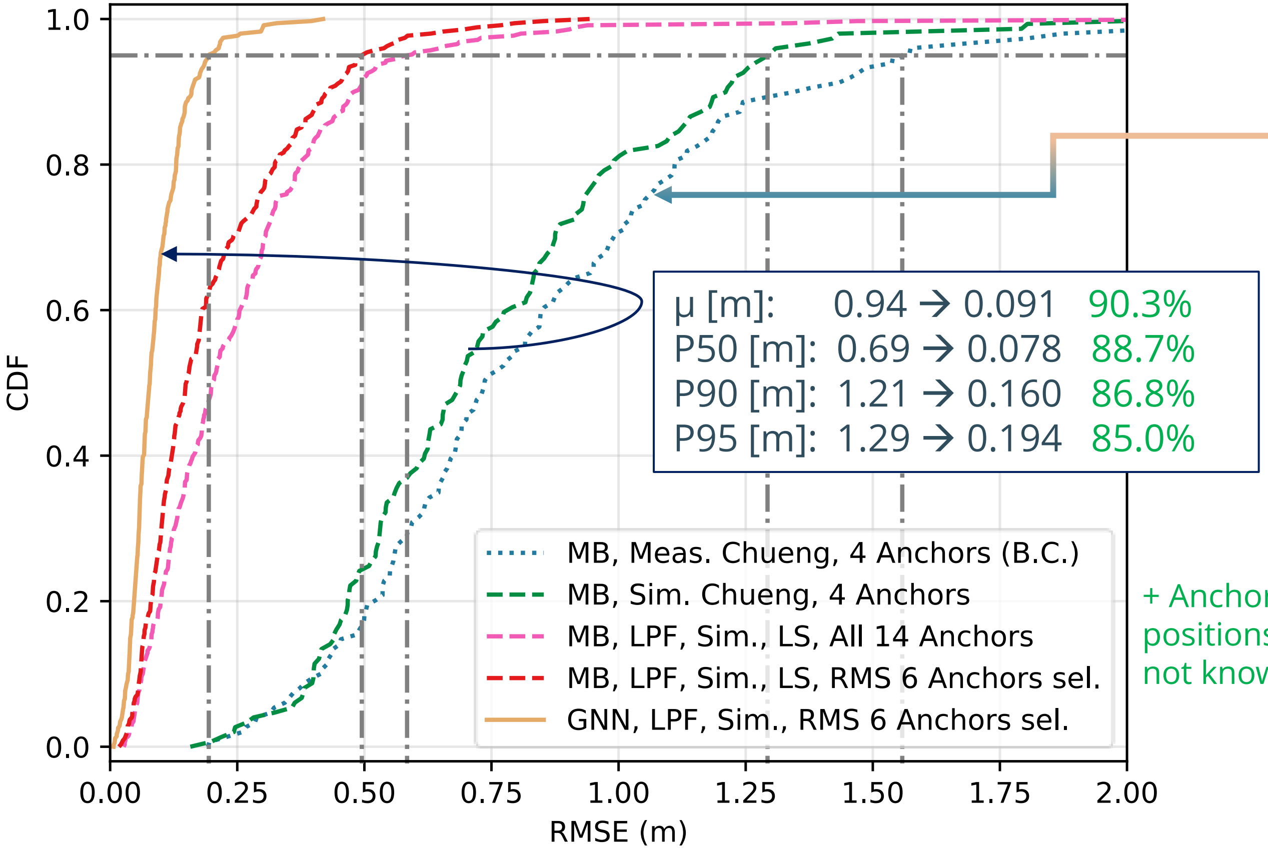


Output

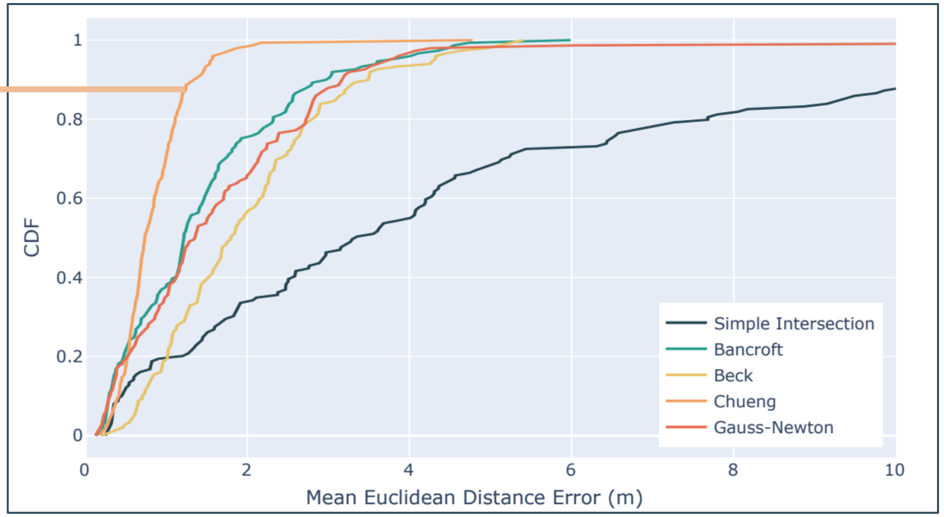
(x, y, z)

POSITIONING IMPROVEMENTS FROM THE START

CDFs of 3D RMSE in the Techtile Environment

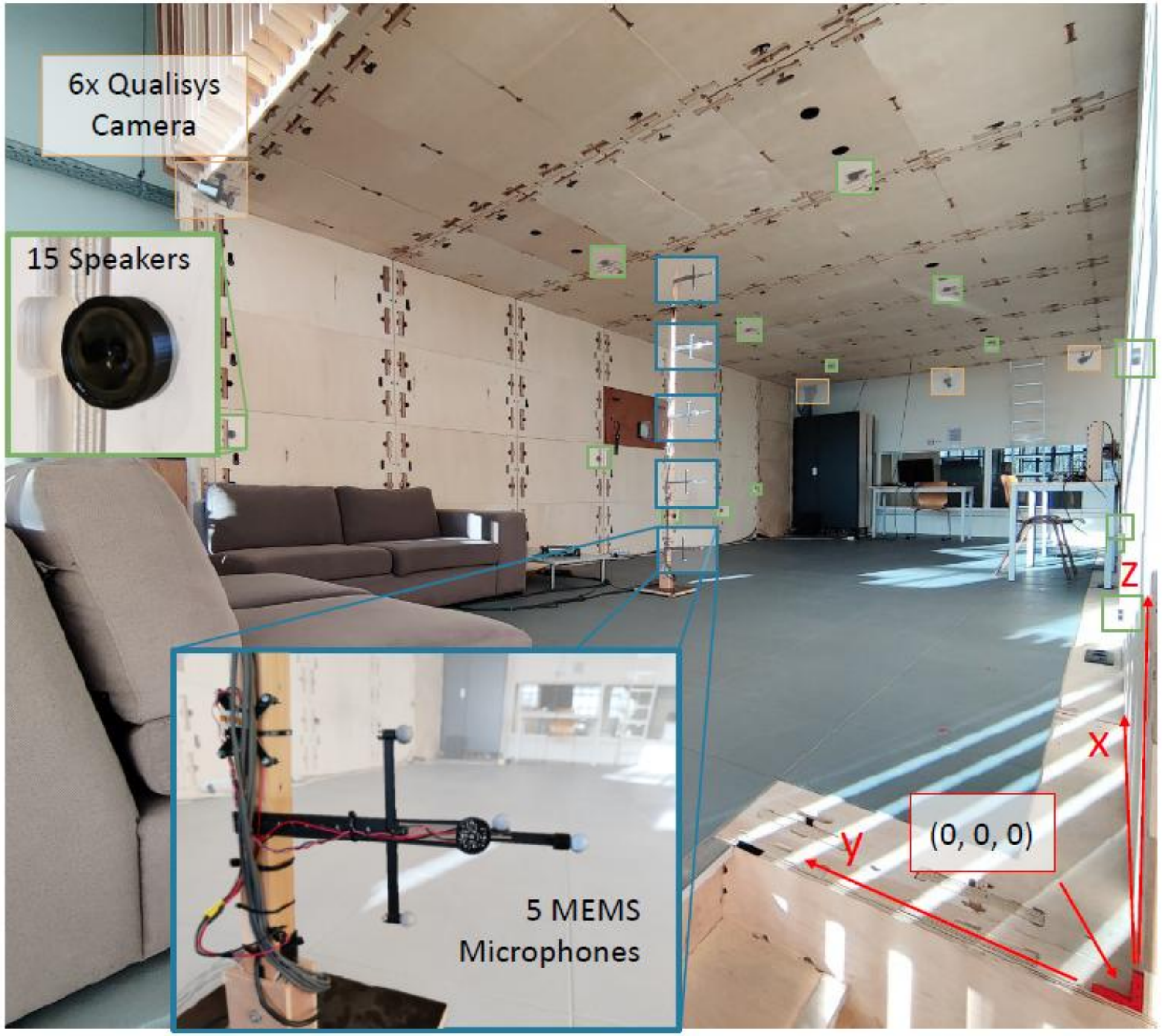


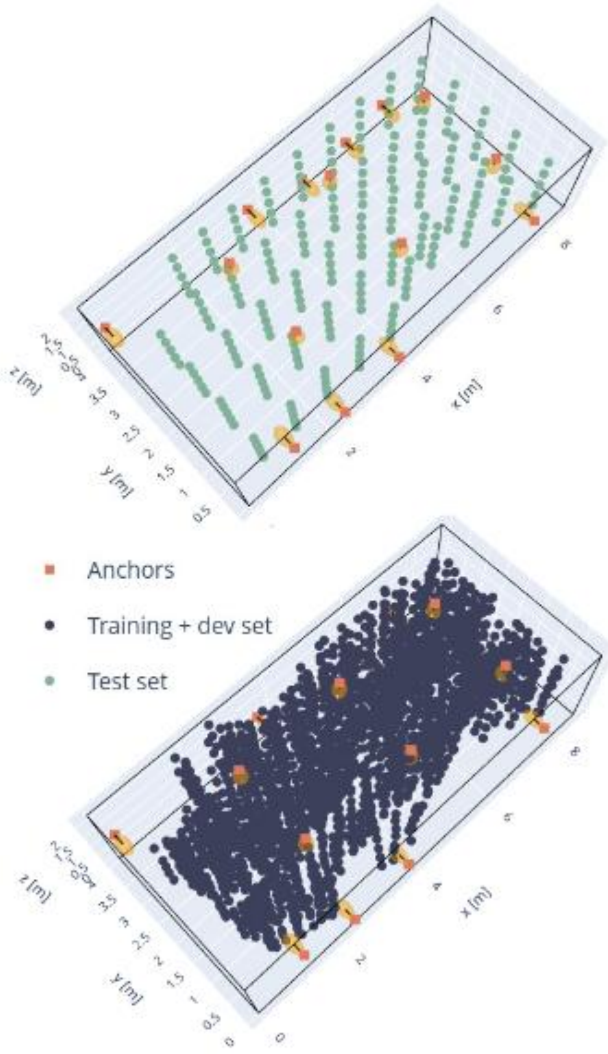
+ Anchor positions not known



B. Cox, C. Buyle, L. Van Der Perre and L. De Strycker, "Towards centimetre accurate and low-power hybrid radio-acoustic 3D indoor positioning: an experimental journey", *2021 IEEE Indoor Positioning and Indoor Navigation (IPIN) CEUR Workshop*, 2021.

THE NEED FOR DATA



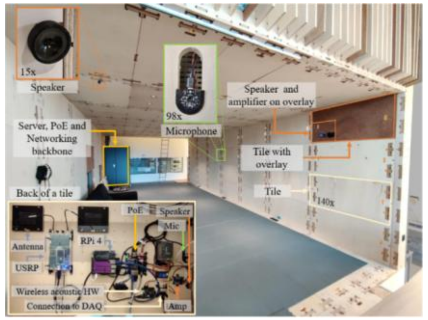


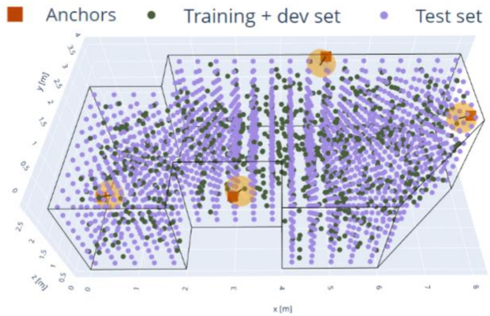
	Set type	Number of samples	Relative (%)
Techtile	Train	2000	78.58
	Development	300	11.79
	Test	245	9.63

Published

POSITIONING IMPROVEMENT STRATEGIES

Methodologies for Experiments





Model Based

Hardware Design

Optimal Anchor Placement

Scaling Distributed Deployment

Position Dependent Anchor Selection

Data-Driven

Input Features

Neural Network Models

Dynamic Assessment

Label-Efficient Self-Supervised

IEEE 15th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP) 2026

Label-Efficient Self-Supervised Acoustic Indoor Positioning Enabling Effortless Deployment

Daan Delabie, Liesbet Van der Perre, Lieven De Strycker
KU Leuven, WaveCore, Department of Electrical Engineering (ESAT), KU Leuven Ghent, 9000 Ghent, Belgium
daan.delabie@kuleuven.be

***Abstract*—Data-driven Indoor positioning systems (IPS) commonly require ground truth (GT) labels and are prone to changing environments. This makes deployment labour-intensive and difficult to scale. This work proposes a label-efficient and self-supervised ultrasonic IPS that removes these requirements by learning the spatial relationships of the environment directly from received channel observations. The method builds on channel charting (CC), using a triplet-based training objective and a graph neural network (GNN) to generate a latent chart that preserves geometric neighbourhoods. An affine alignment step maps the learned chart to physical space using only a minimal number of reference points. The system is implemented and evaluated in an indoor testbed. Results demonstrate that the CC-based approach achieves positioning accuracy close to conventional supervised learning while requiring neither GT labels nor anchor coordinate knowledge, highlighting its potential for effortless and scalable deployment. Additional learning during operation mitigates the difficulties arising from a dynamically changing environment.**

***Index Terms*—Localization, Indoor environment, Ultrasonic applications, Acoustics, Neural networks, self-supervised learning**

I. Introduction

Indoor positioning systems (IPSs) are increasingly important e.g. in logistics, industrial automation, and robotics. While most research focuses on improving positioning accuracy, the practical deployment effort is often underestimated. Conventional systems typically require precise anchor placement and labeled ground truth (GT) data for training and calibration, making installation labour-intensive, time-consuming, and sensitive to environmental changes. Transfer learning (TL) can reduce this burden but still relies on reference measurements and manual setup [1]. This work addresses the need for effortless deployment by exploring label-efficient and self-supervised learning strategies. The approach is compatible with the ultrasonic energy neutral (EN)-device IPS demonstrated in [1].

Most IPS methods assume at least partial knowledge of anchor positions, dedicated calibration or labelling and rely on additional sensing modalities such as cameras [2], Light Detection and Ranging of Lasers (LiDARs) [3], [4], or inertial measurement units (IMUs) [5] for auto-calibration. These solutions increase deployment cost and system complexity. Relative positioning does close the gap to effortless deployment [6]. Yet anchor placement should partially be known to make absolute positioning possible and ranging errors can easily lead to incorrect relative positioning. More recently, self-supervised learning approaches are developed to infer spatial structure without explicit labels [7], [8]. Channel charting (CC) is a notable example, enabling relative spatial learning directly from channel observations without GT labels [9]. This is also a relative positioning system, yet a simple conversion to absolute positioning is possible. CC is particularly attractive for long-term deployment, as mobile nodes (MNs) can provide data organically during operation without manual intervention. However, CC has not yet been demonstrated for ultrasonic IPSs. In this work, we compare conventional supervised learning with CC-based training using measurements and show that CC achieves performance close to supervised models, demonstrating its value for effortless deployment.

Section II describes the signaling and hardware setup of the acoustic IPS. Section III reviews the CC framework, and is followed by Section IV presenting the measurement campaign and results. Section V discusses implications, and Section VI concludes the paper.

II. Positioning System and Signaling Design

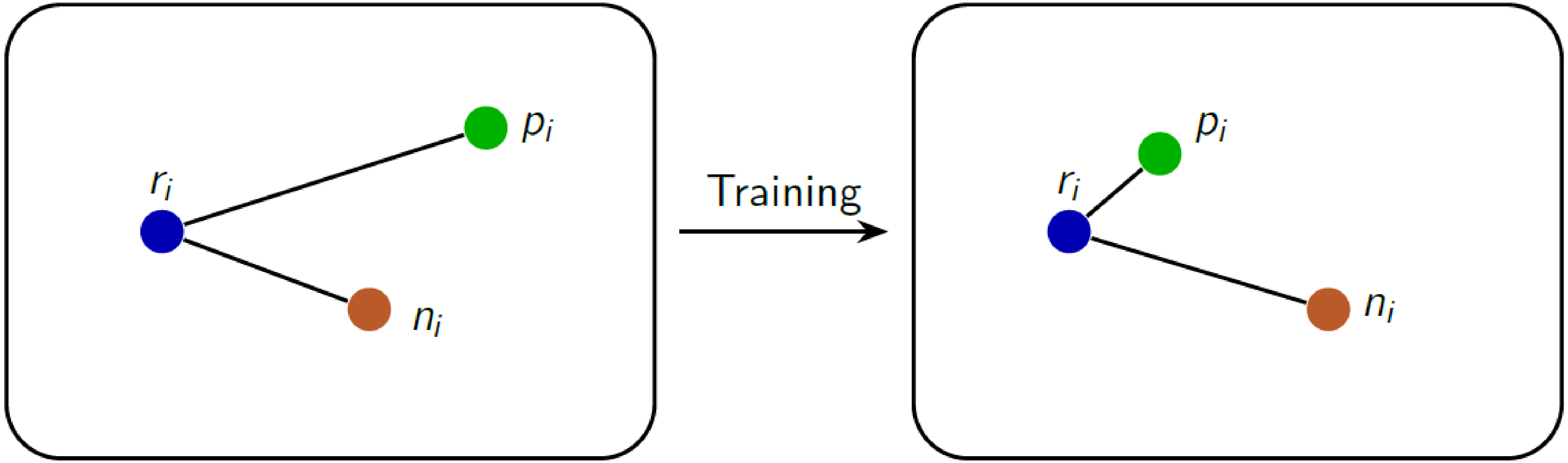
The development and validation of the novel label-efficient self-supervised positioning method, starts from a well-studied hybrid RF-acoustic IPS [1]. A set of fixed anchor nodes (ANs), which are speakers with unknown positions deployed throughout the indoor environment, periodically transmit 30 ms linear ultrasonic chirps, sweeping frequencies from 20 kHz to 40 kHz. The chirps are chosen for their favourable pulse-compression properties, providing robustness against noise and enabling accurate ranging using low-cost, low-power commercial components. At the end of each transmission, a single RF synchronization pulse is emitted. This pulse simultaneously triggers all MNs to sample a short (1 ms) snapshot of the received acoustic signal. The brief sampling window in combination with RF-backscattering of the captured audio and edge-processing, keeps the energy expenditure at the MNs low, supporting batteryless, energy-neutral designs powered through RF wireless energy transfer [1]. In a model-based (MB) solution each MN processes the acquired audio segment by cross-correlating it with a the original chirp to estimate the propagation delay and, consequently, the range. For each MN 6 ANs are selected based on received signal strength (RSS) [1], from which it will use the data. The conventional MB multilateration method converts these distances into 3D position estimates via a least squares (LS) solver. However, due to multipath components (MPCs) and the fact

SEMI SELF-SUPERVISED LEARNING WITH CHANNEL CHARTING (CC)

- Learn a chart: arrange signals in a map-like way
- Alignment of chart space to physical space

$$\delta_{Phy}(\boldsymbol{a}, \boldsymbol{b}) \sim \delta_{CC}(\boldsymbol{a}', \boldsymbol{b}')$$

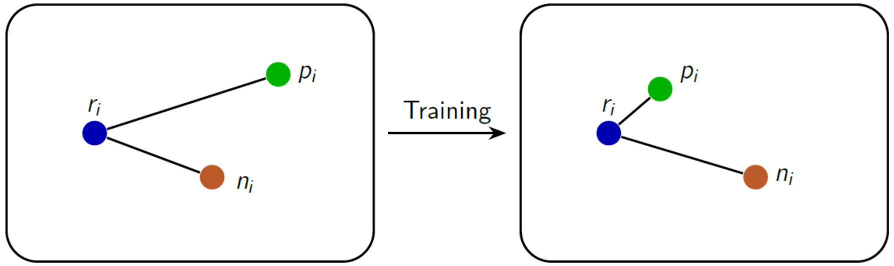
(pseudo-)distance

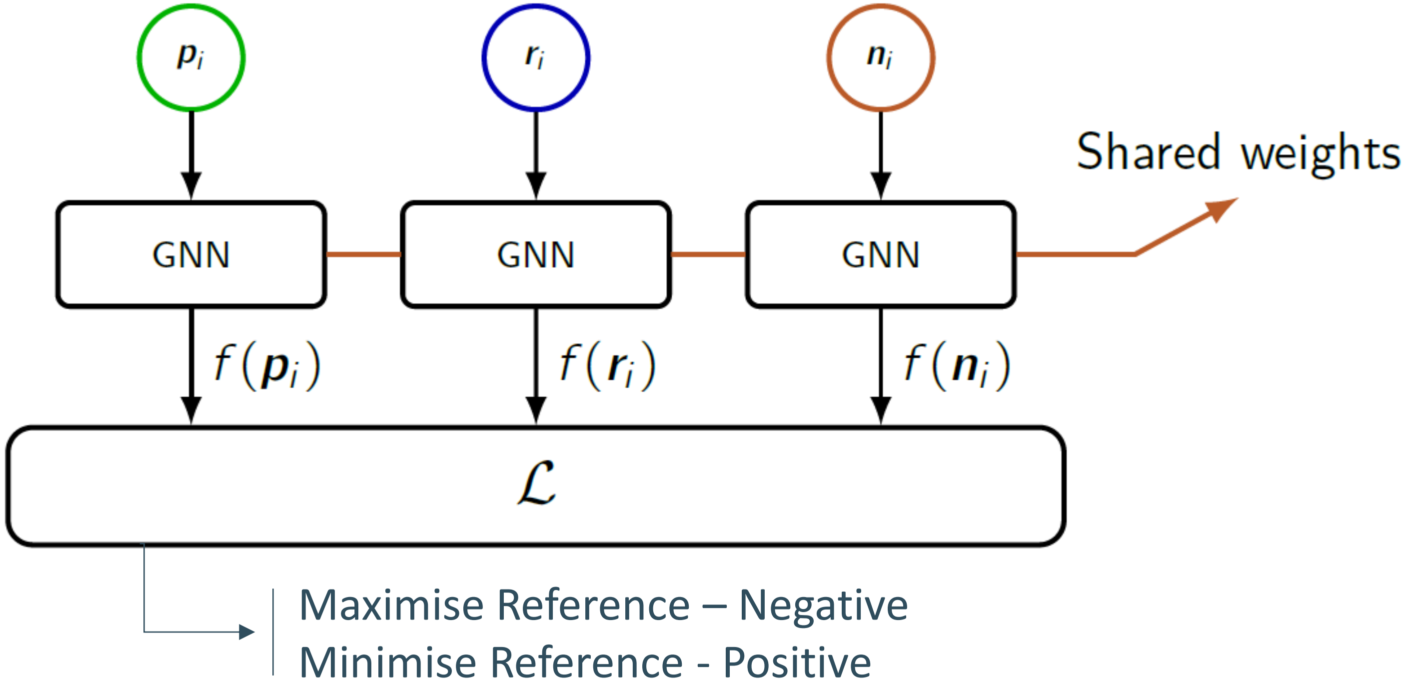


TRIPLET LOSS PRINCIPLE

- Learn a chart: arrange signals in a map-like way
- Alignment of chart space to physical space

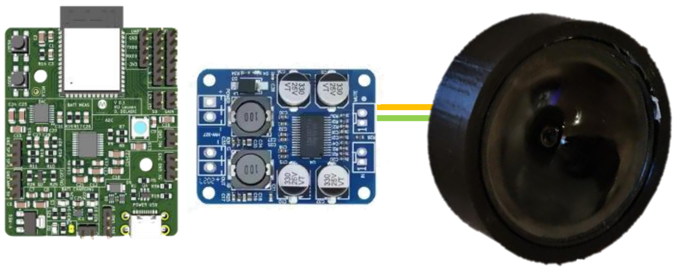
$$\delta_{Phy}(\boldsymbol{a}, \boldsymbol{b}) \sim \delta_{CC}(\boldsymbol{a}', \boldsymbol{b}')$$

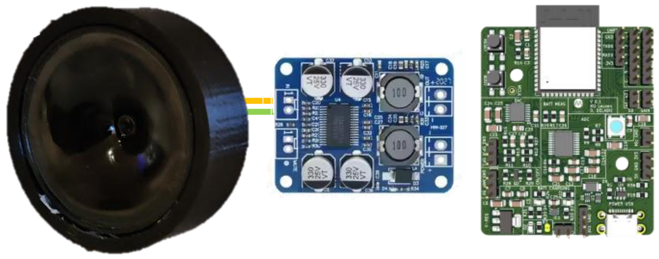


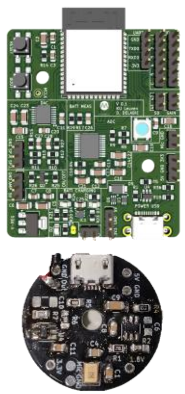


HARDWARE SETUP

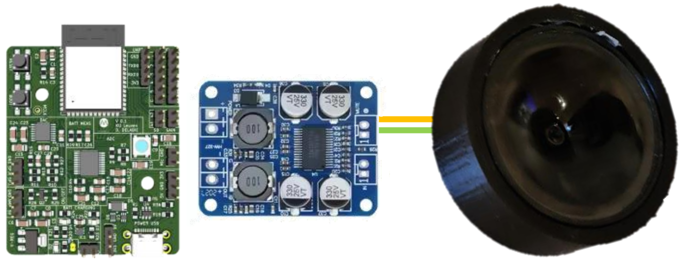
Anchor (AN)



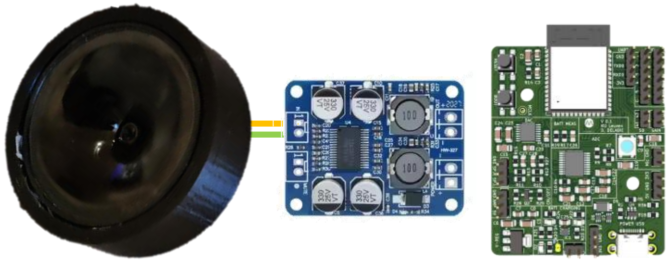




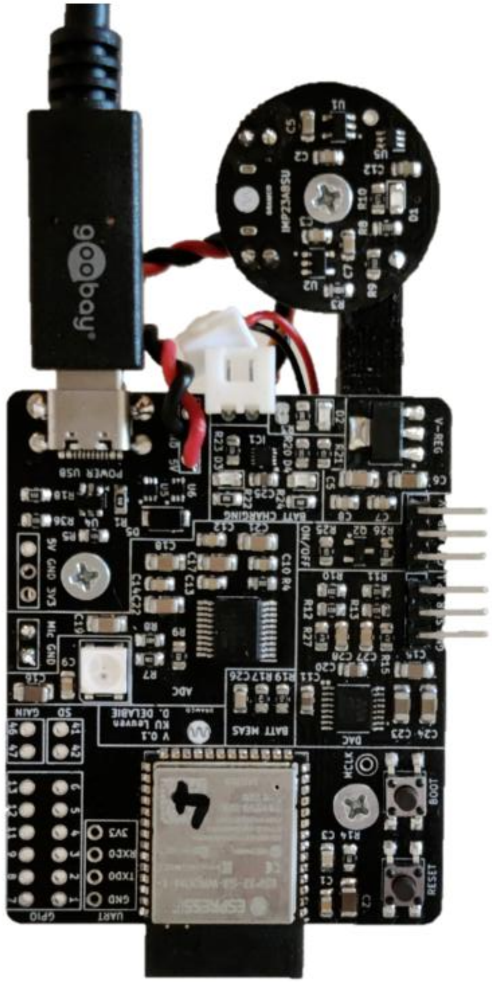
Mobile Node (MN)

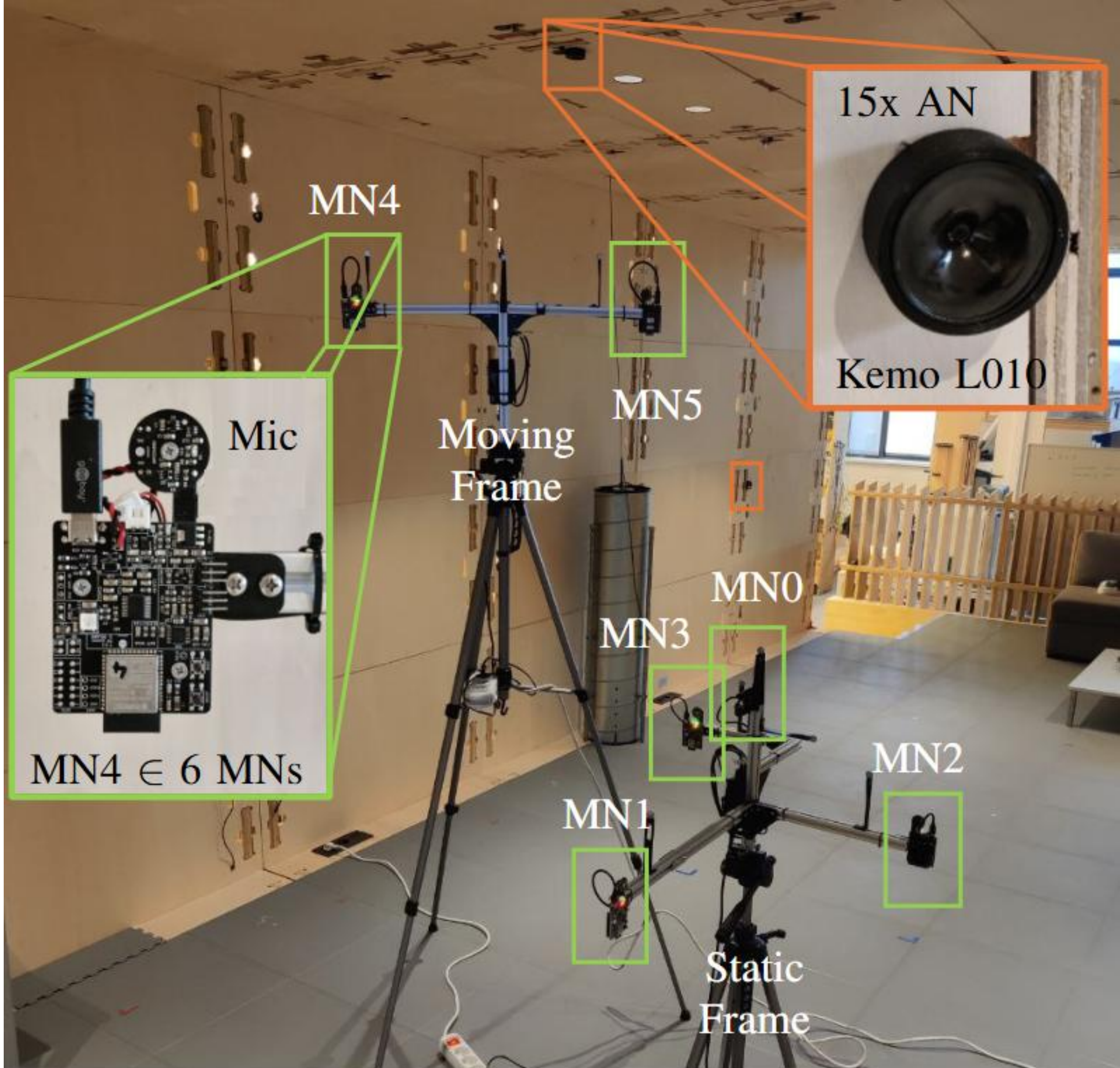


Dispatcher

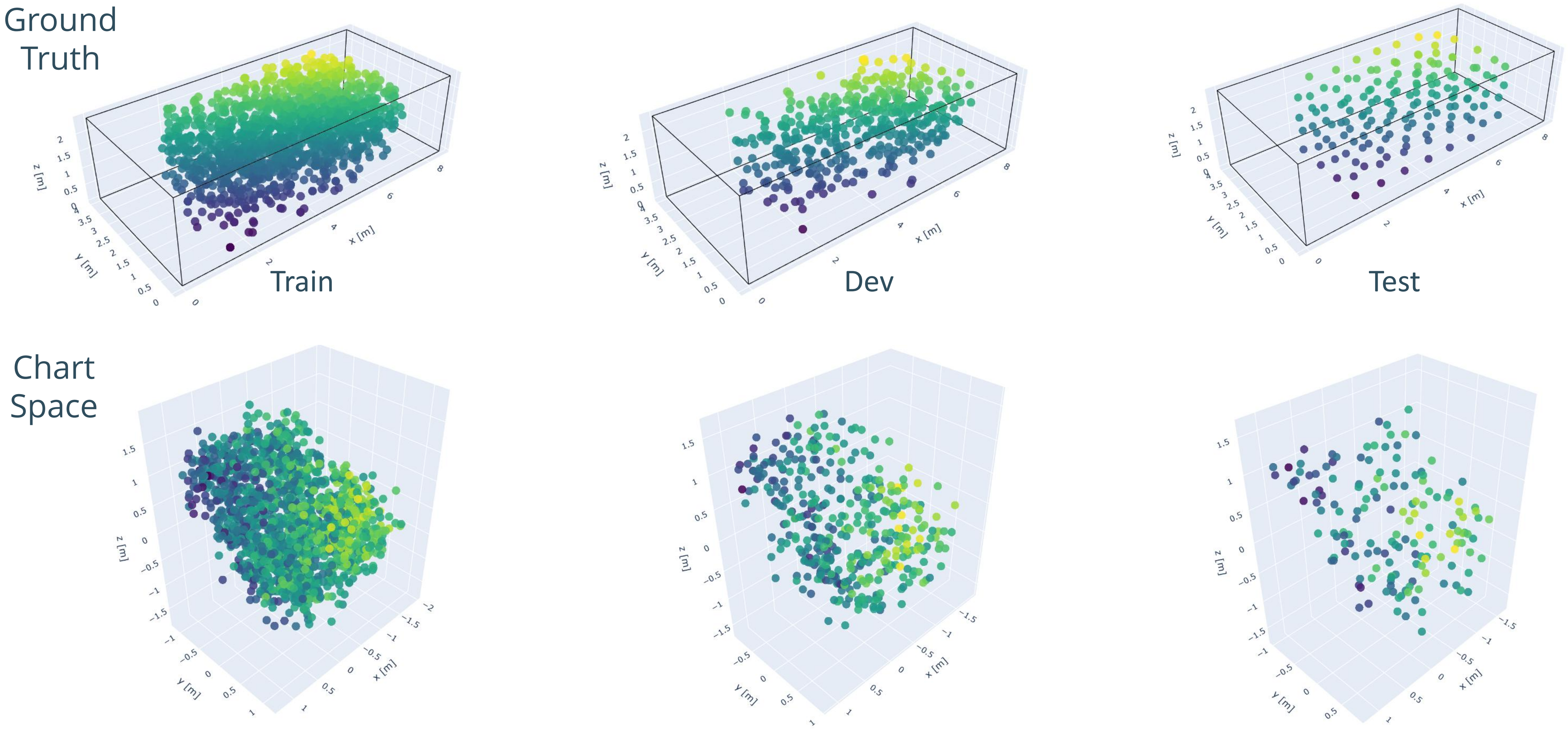


WIRELESS POSITIONING NODES



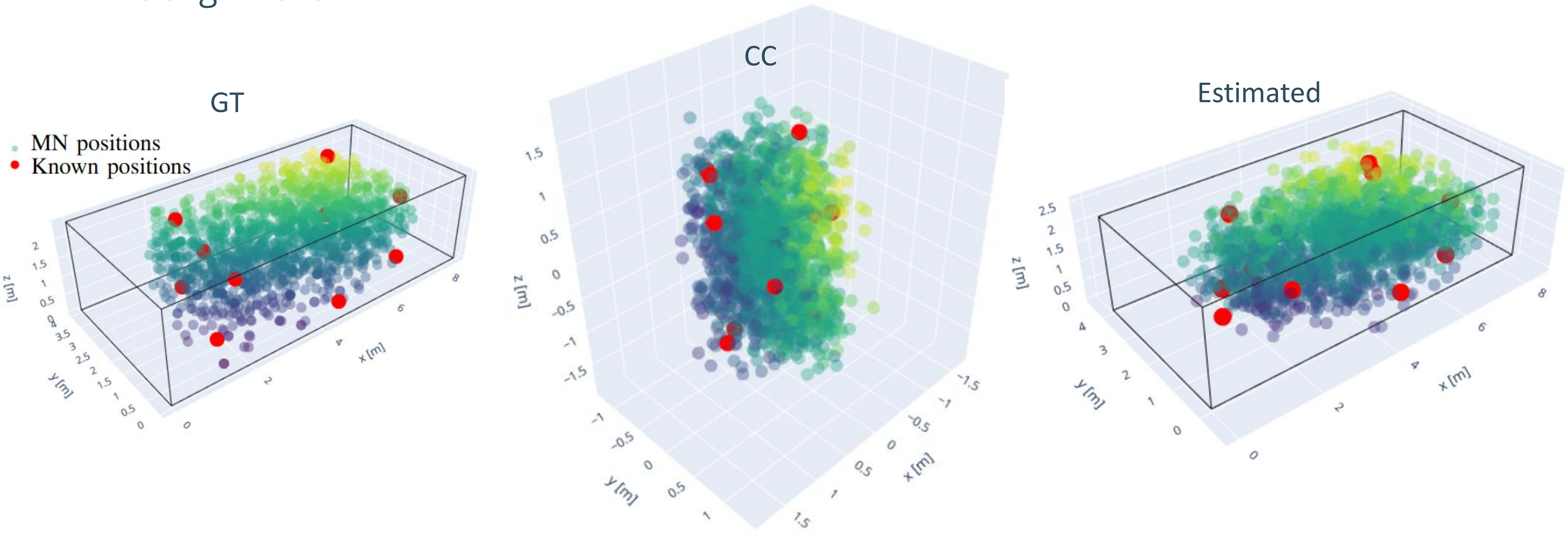


DATA → CHART SPACE



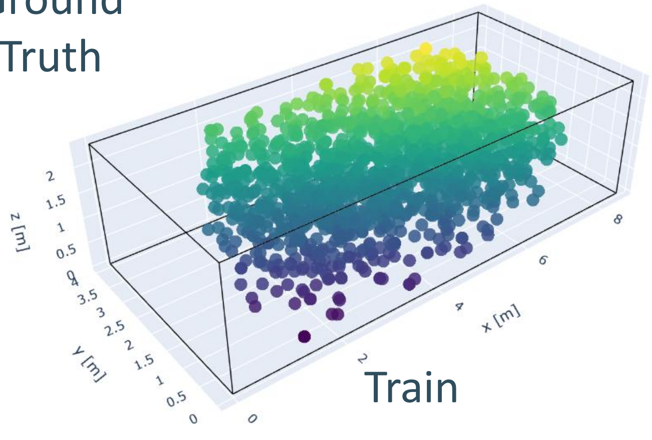
FROM CHART SPACE TO PHYSICAL SPACE

- Get some reference points e.g. 10 with known positions
- Affine alignment

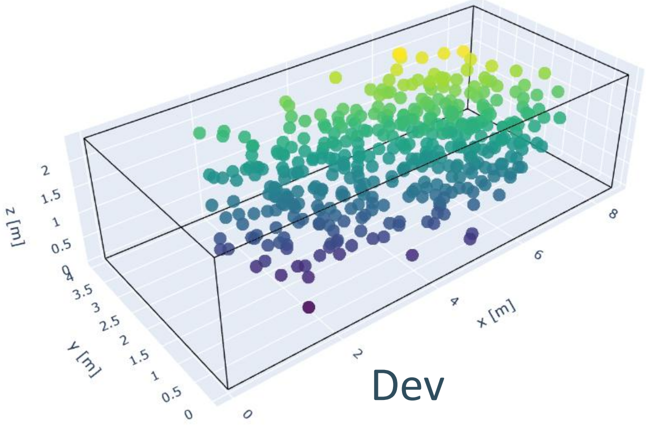


DATA → CHART SPACE → PHYSICAL SPACE

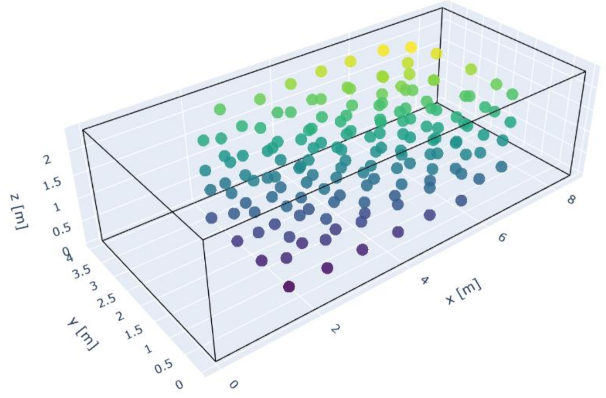
Ground Truth



Train

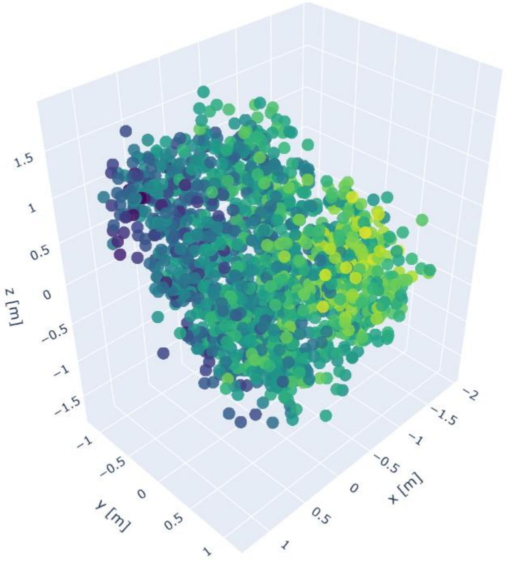


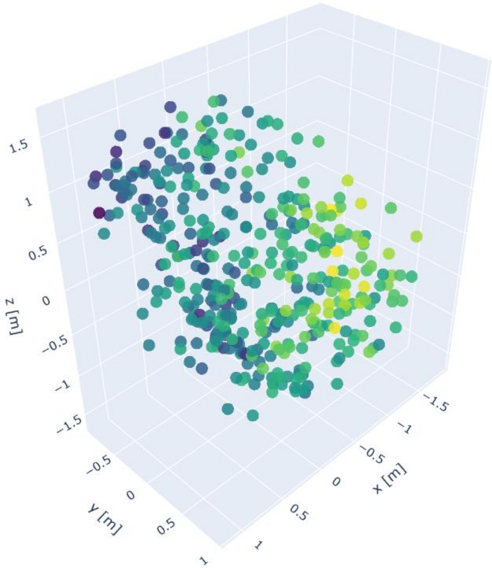
Dev

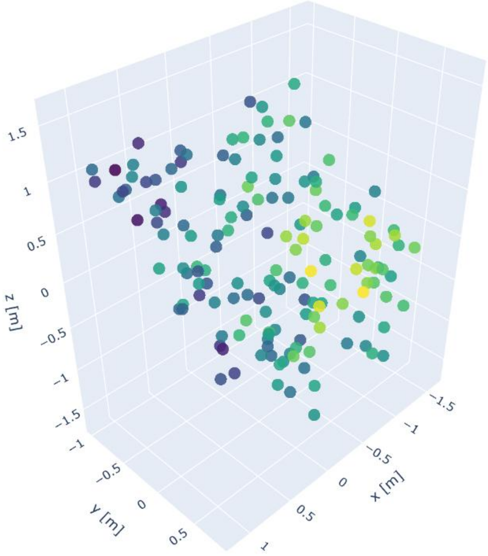


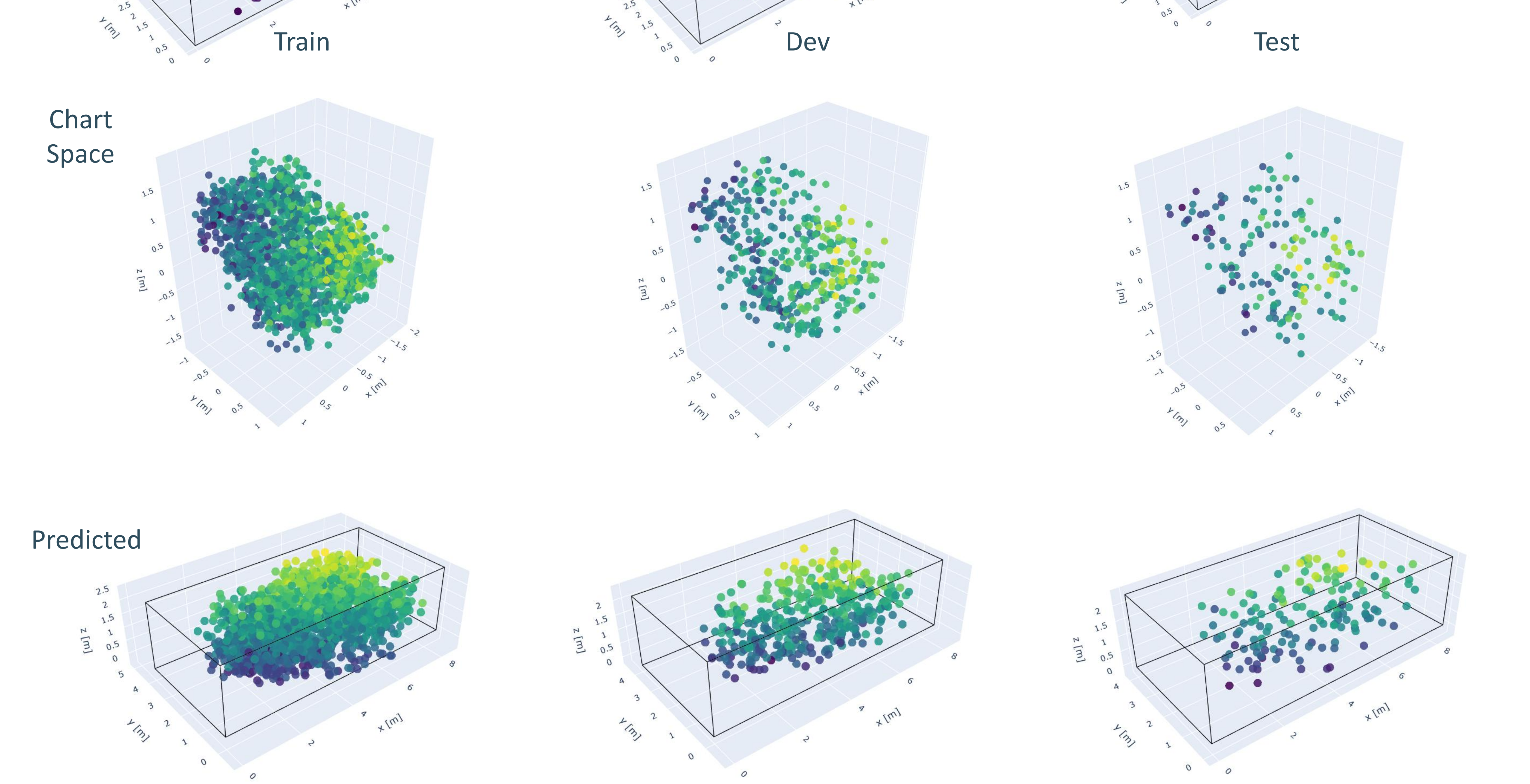
Test

Chart Space

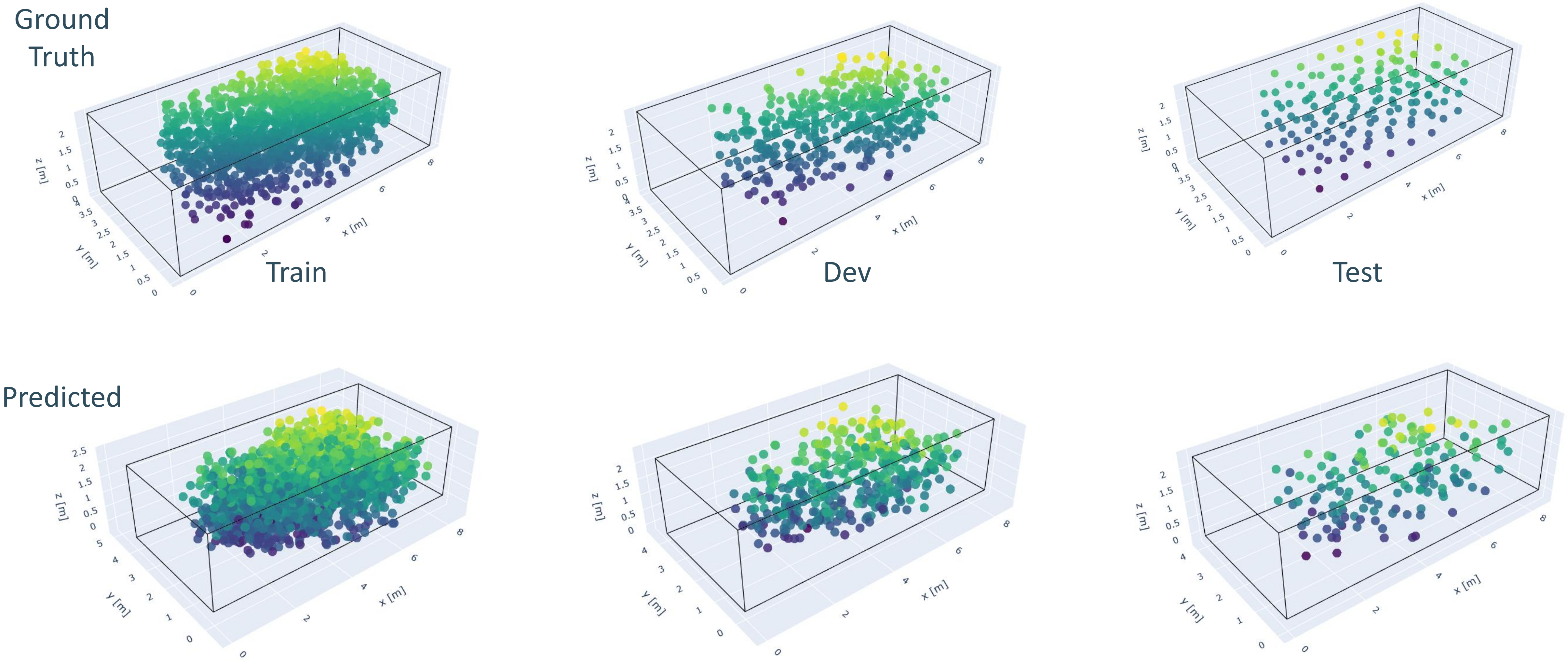




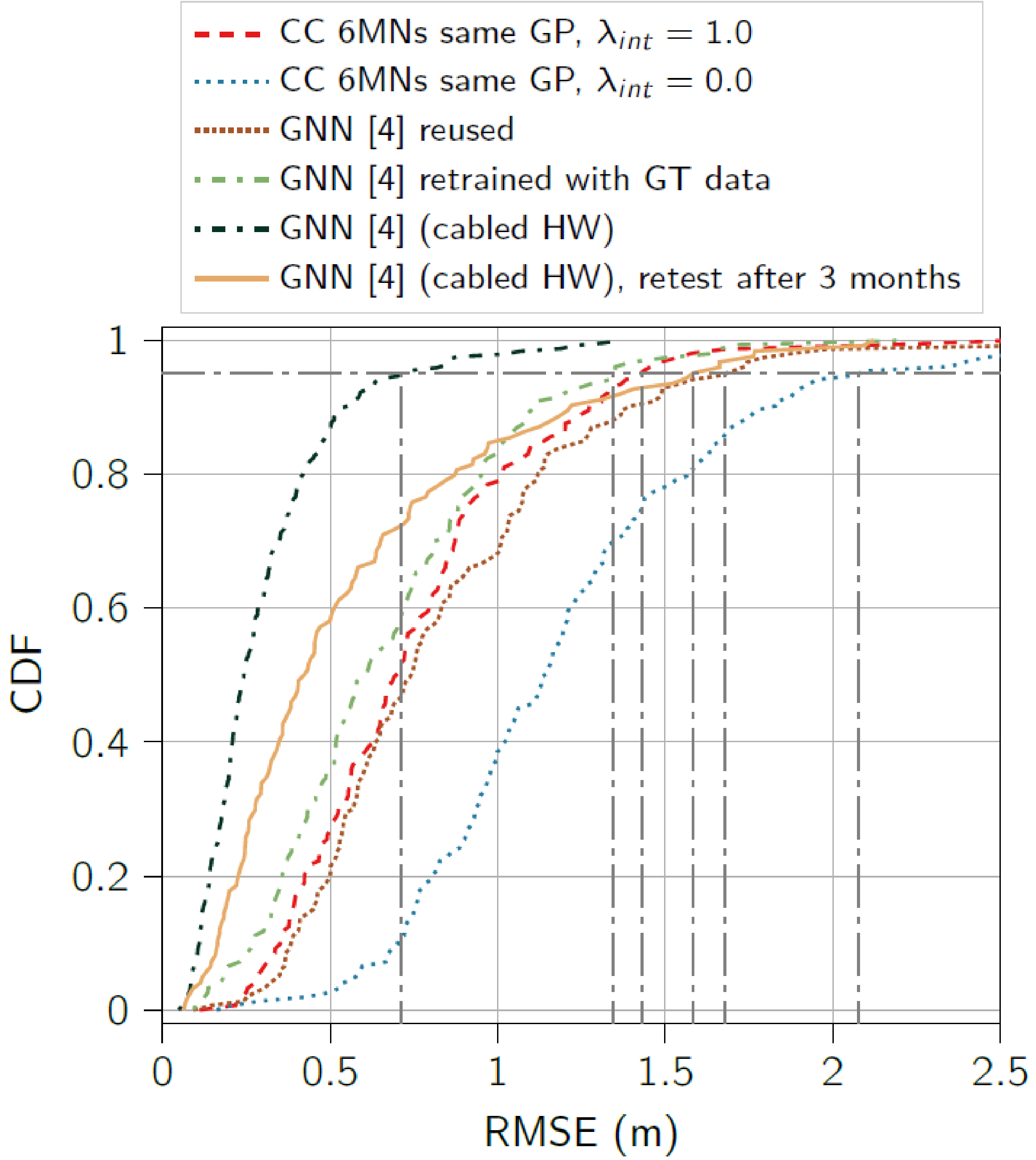



Train
Dev
Test
Chart Space
Predicted
x [m]
y [m]
z [m]

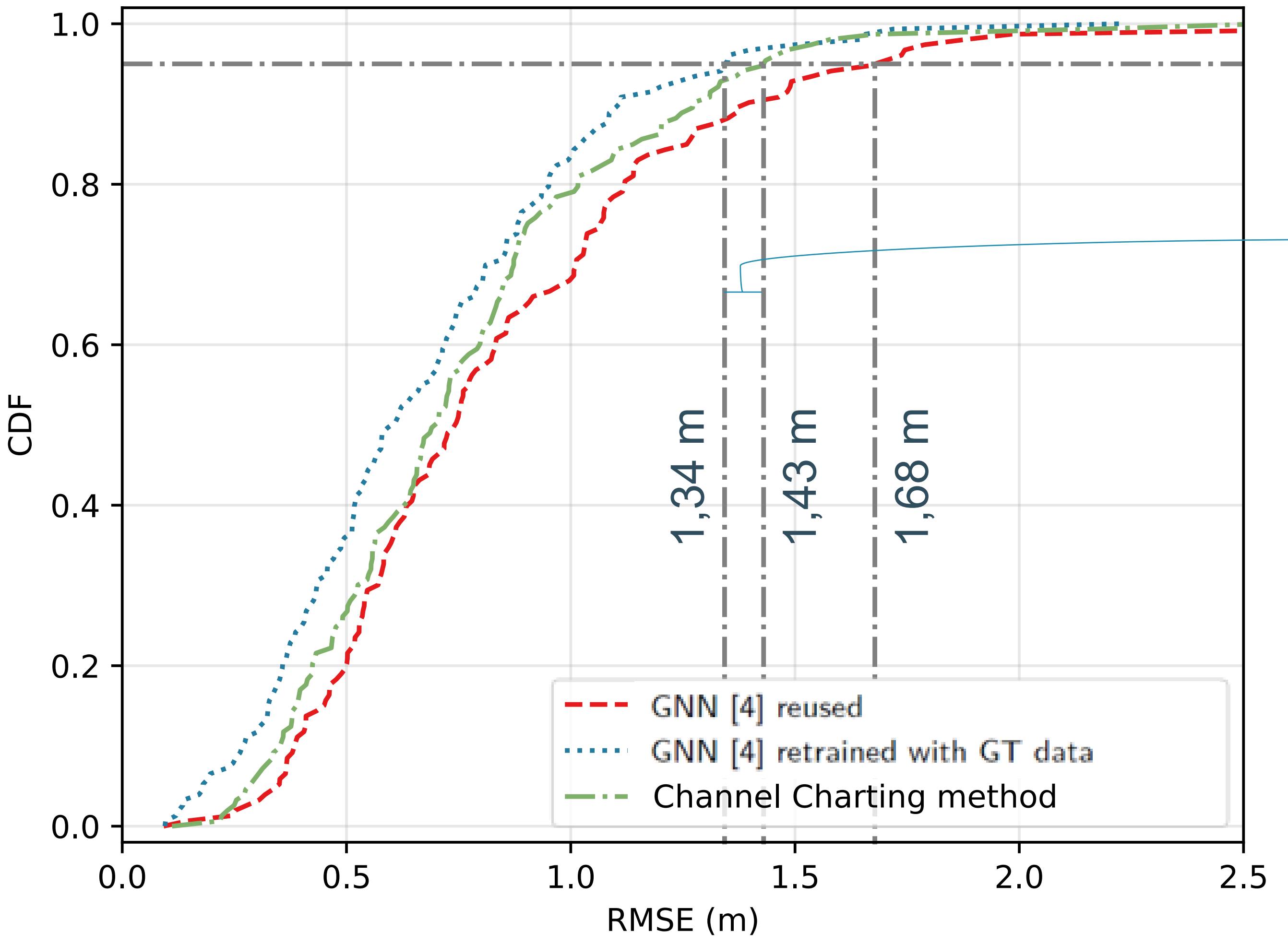
DATA → CHART SPACE → PHYSICAL SPACE



CC VS GT-GNN TRAINING



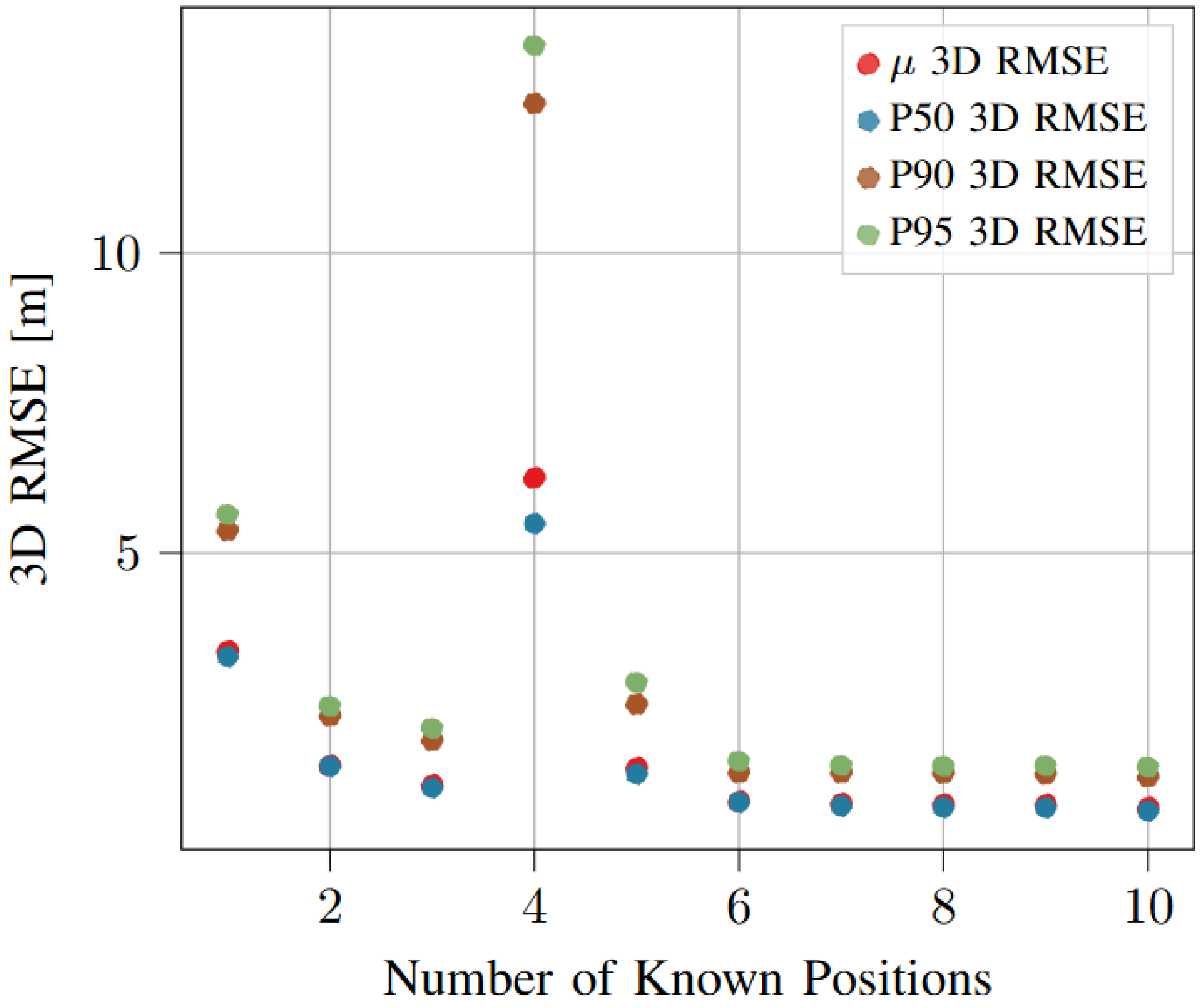
3D RMSE RESULTS



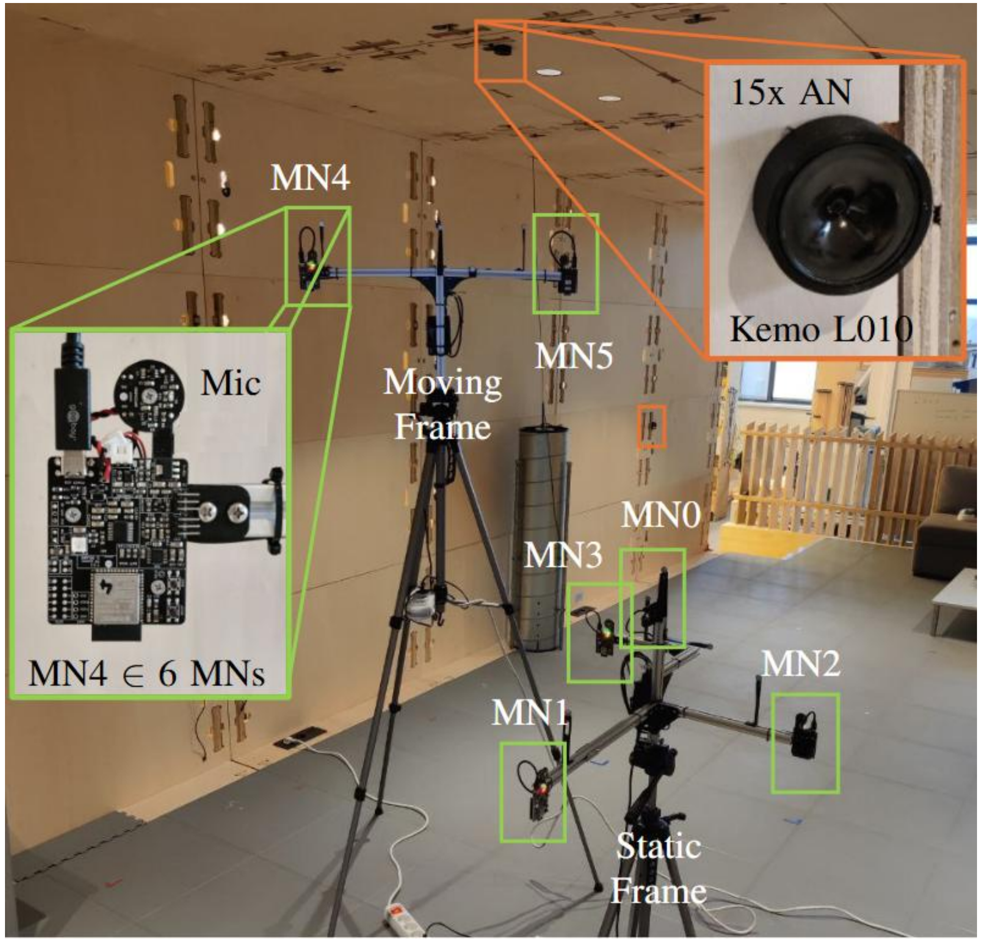
P95: 6,72%

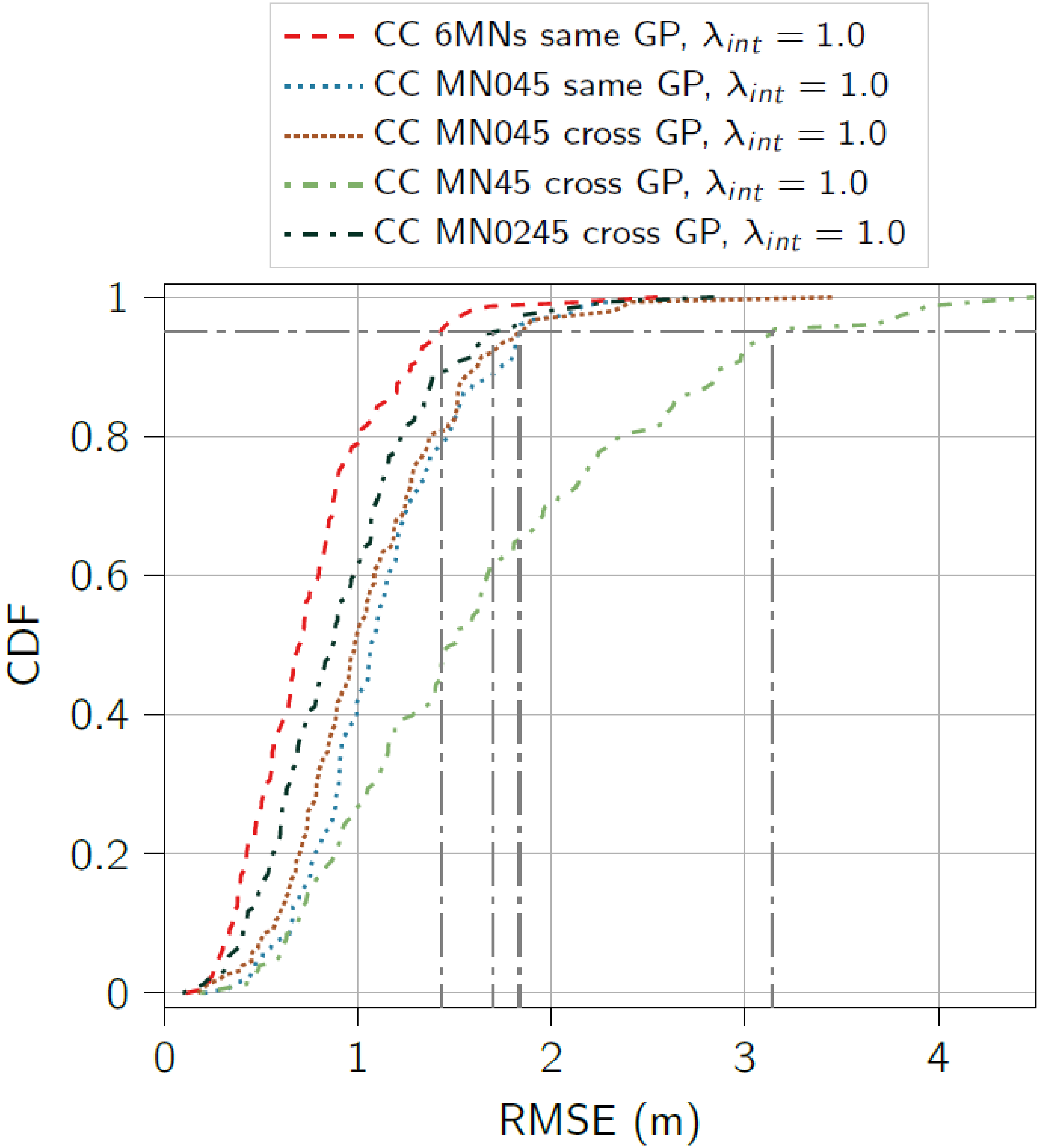
Label-efficient and self-learnable

EVOLUTION OF ACCURACY IN FUNCTION OF KNOWN GT POSITIONS



3D RMSE RESULTS: CC FLAVOURS





CONCLUSION

- Support for EN devices
- Accurate
- Scalable and low-cost
- Self-learnable and label-efficient