

Mobile Robot-Assisted Collection of a 5G Measurement Indoor Dataset

Jan Faigl¹ Vsevolod Hulchuk¹ Simon Uhrmann² Rudolf Szadkowski¹ Markus Peterhansl²

Abstract—The paper presents a 5G measurement dataset collected using a mobile robotic platform in both indoor and outdoor environments. The dataset captures real-world characteristics of 5G infrastructure under mobility, including spatial variations in signal quality across heterogeneous deployment scenarios. Measurements were acquired using the mobile robot equipped with onboard sensors for localization, enabling accurate georeferencing of signal measurements in both indoor and outdoor settings. The resulting dataset supports research in signal propagation modeling in complex environments, 5G performance evaluation, and data-driven analysis in realistic deployment scenarios.

I. INTRODUCTION

Signal propagation modeling is the problem of designing a suitable formula that describes how a radio signal is weakened by the environment and by obstacles. Although propagation models are grounded in electromagnetic field theory, strong empirical evidence remains essential for deriving practically usable models that can quickly estimate expected signal availability within a given area. Data-driven approaches [1] therefore require datasets collected in realistic setups, and several such works have been reported in the literature [2], [3]. Furthermore, mobile robots can directly benefit from 5G network features, and experimental deployments have already been demonstrated across a wide range of robotics applications, as reported in [4].

Extensive datasets of 5G measurements are collected to provide data allowing network analysis, performance prediction, and data-driven modeling of key connectivity indicators across time and location [5]. Besides, mobile robots can be employed to collect data in autonomous or teleoperated mode together with 3D LiDAR measurements, enabling environment modeling [6].

In a similar scope to [6], we present a dataset from a private indoor 5G infrastructure, where a mobile robot is employed to LiDAR-based georeference received 5G signal strength measurements. Furthermore, 3D LiDAR mapping is used to generate a point cloud representation of the environment, supporting data-driven propagation modeling in a real-world indoor scenario.

¹The authors are with the Faculty of Electrical Engineering, Czech Technical University, Technická 2, 166 27 Prague, Czechia. {faigl.j, szadk.rud}@fel.cvut.cz, hulchvse@student.cvut.cz

²The authors are with the Institute for Applied Informatics, Deggendorf Institute of Technology, Grafenauer Str. 22, 94078, Freyung, Germany. {simon.uhrmann, markus.peterhansl}@th-deg.de

The presented research was supported by the Ministry of Education, Youth and Sports of the Czech Republic (MEYS) under Project No. LUABA24064 and the Bavarian State Ministry of Education, Science and the Arts (StMWFK) under project No. BTHA-JC-2024-59 as Joint Czech-Bavarian Research Project.

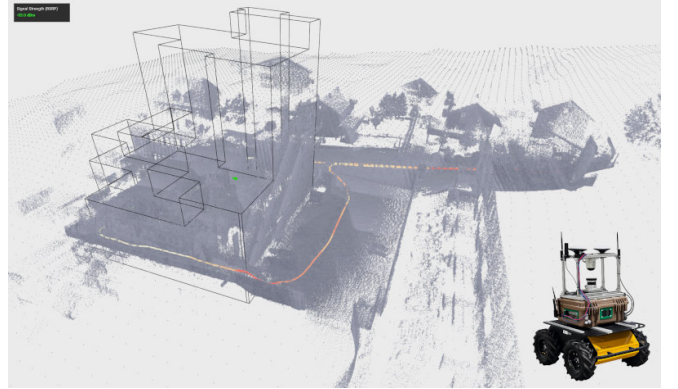


Fig. 1. An overview of the collected signal strength along the robot's traveled path inside and outside the building. The created 3D point cloud map from LiDAR measurements is globally aligned with publicly available terrain elevation and 3D building models.

The collected dataset is intended to provide realistic data for studying signal availability prediction within a mobile robotics setup. In particular, we aim to employ a data-driven approach [7] for non-5G communication channels.

Since relevant 5G datasets collected by mobile robots in indoor environments are not yet widely available, we present the collected and processed data (see Fig. 1) as a work-in-progress report to make it available to other researchers.

The rest of the paper is structured as follows. A summary description of the 5G infrastructure setup is provided in the following section. A brief overview of the employed mobile robot platform and localization method is presented in Section III. The dataset is described in Section IV and a conclusion is presented in Section V.

II. 5G INFRASTRUCTURE SETUP

The 5G campus network is based on a decentralized architecture with a centralized core network. At the local site at Deggendorf Institute of Technology, various user equipment such as smartphones, laptops, IoT devices, and robots are wirelessly connected via two *CableFree 5G RRU* (Radio Remote Unit) units. The RRU converts digital baseband signals to radio-frequency signals for wireless transmission and vice versa. It is installed close to the antenna to minimize cable losses and contains power amplifiers, receivers, and filters. The RRU connects the baseband unit to the router via an Ethernet cable and handles the physical-layer radio transmission in the licensed frequency band. These units operate in *5G NR Standalone* mode within the 3.7 GHz to 3.8 GHz frequency band and provide indoor coverage of up

to 300 m through their 2×2 MIMO configuration and 10 W total output power.

Each RRU unit is connected to a *Robustel R5020* industrial router, which serves as a local gateway, to allow internet connectivity. These routers feature dual-SIM functionality with automatic failover capability and native *WireGuard* VPN support. The symmetrical configuration with two RRU units provides both redundancy and increased network capacity.

The connection between the local campus network and the central core network is established via a secure *WireGuard* VPN tunnel running over a cellular internet connection with a maximum bandwidth of 100 Mbit s^{-1} . The VPN ensures that both control-plane signaling (*NGAP* over *SCTP*) and user-plane data (*GTP-U* over *UDP*) are securely transmitted across the public internet.

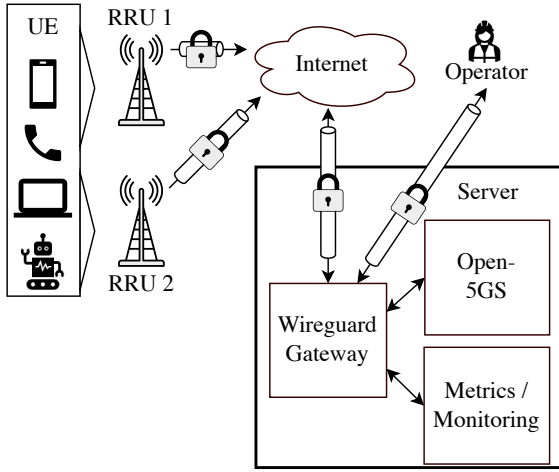


Fig. 2. **5G Setup** for the 5G campus network at DIT.

The VPN gateway forwards the encrypted traffic to the Open5GS core network. It runs on an *Ubuntu Server 22.04 LTS* and comprises all necessary network functions according to *3GPP Release 16*, including *AMF* for authentication and mobility management, *SMF* for session management, *UPF* for user plane forwarding, as well as additional functions such as *NRF*, *PCF*, and *UDM*. An integrated monitoring system continuously tracks the uptime and performance of the entire network. Finally, access to the public internet is provided via the *N6 interface* of the *UPF*, with a robot operator exemplarily represented as an external user, trying to control a robot connected as UE to 5G. A schematic visualization of the architecture is depicted in Fig. 2.

III. MOBILE ROBOTIC MEASUREMENT PLATFORM

The experimental platform utilized is a Husky A200 wheeled robot equipped with a custom measurement system, see Fig. 3. The system consists of a *Local Area Network* (LAN) connecting a computational unit (*MSI Cubi NUC with Intel Core i5*), a modem (*Robustel 5020*), and a LiDAR

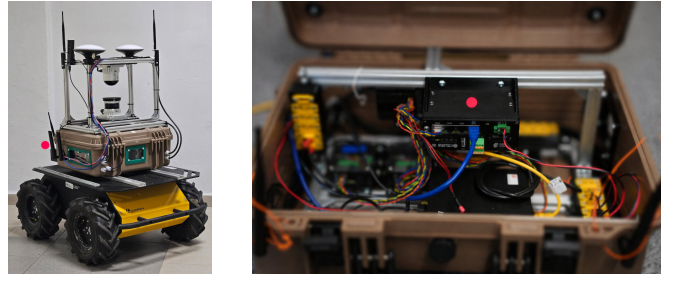


Fig. 3. Mobile robot employed in data collection of 5G measurements using Robustel 5020 router. A small red disk marks the position of the antenna and router.

(*Ouster OS1-128*) with an in-built 6-axis *Inertial Measurement Unit* (IMU). The LiDAR and IMU provide measurements used to reconstruct a local 3D model and localize the platform during data post-processing. The modem connects to a *Base Transceiver Station* (BTS) via a 5G network to measure the *Reference Signal Received Power* (RSRP). The computational unit runs the Robot Operating System (*ROS Noetic*), which manages both data collection and robot teleoperation.

A. Robot Localization and Data Georeferencing

An adaptation of the LIO-SAM (LiDAR-Inertial Odometry and Mapping) [8] has been employed to create a local 3D point cloud map and estimate the robot's position. The contributing sensors consist of the LiDAR and its IMU. The resulting point cloud map has a resolution of 0.15 m.

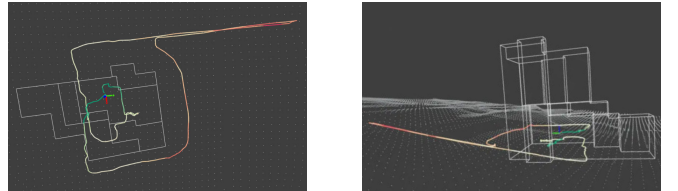


Fig. 4. A projection of the localized RSRP measurements collected by the mobile robot into a 3D building model of the OBD [9].

Global Alignment: We utilized *Open Bavarian Data* (OBD) [9] to obtain terrain elevation and 3D building models. These were sampled into point cloud models for further geo-referencing. The available 3D building model is used in visualization as depicted in Fig. 4.

Transformation: An initial guess for the local-to-global transformation was established using 4 manually selected correspondences. We then refined the initial transformation using the *Generalized Iterative Closest Point* (gICP) to obtain a precise transformation, allowing us to transform the robot's traveled path from local to global GPS coordinates.

IV. DATASET DESCRIPTION

5G measurements are collected using a developed ROS Node responsible for reading out connection parameters from the Robustel R5020 router. It includes the information about the operator, which in our case is BTHA TCF BTHA 5G, see Fig. 5. The signal strength information is provided as

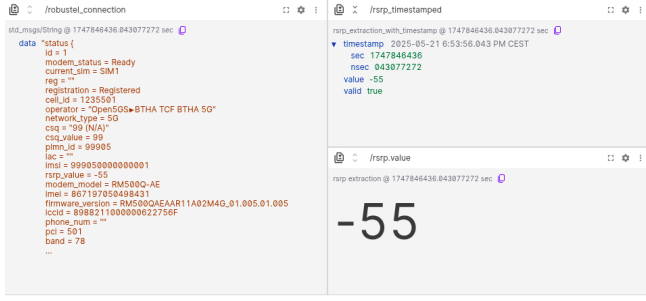


Fig. 5. A visualization of the raw data readouts from the Robustel R5020 under `robustel_connection` topic.

the RSRP at 1 Hz. The received data are then time-stamped and shared as the topic `rsrp_timestamped`.



Fig. 6. The DIT building where the 5G measurements have been taken.

The data have been collected within the DIT building and its nearby neighborhood, as depicted in Fig. 6. LiDAR data

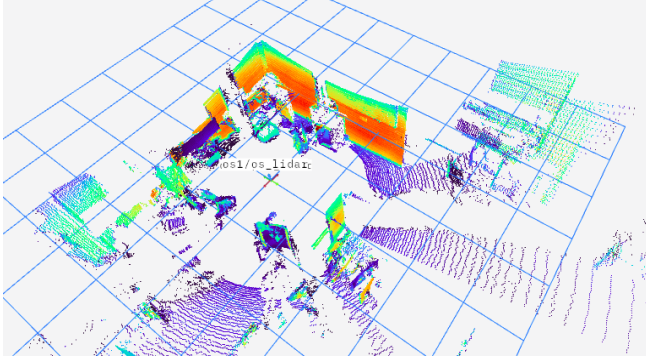


Fig. 7. Raw LiDAR data showing the surroundings of the robot.

are used for mobile robot localization and for building an environmental map. Raw LiDAR data from a single 3D scan is visualized in Fig. 7. The collected RSRP values along the robot path are plotted in Fig. 8.

Dataset¹ consists of RSRP values and their corresponding global GPS coordinates. Furthermore, a 3D point cloud map

¹The data are available at <https://purl.org/crl/outputs/luaba24-5g25f>.

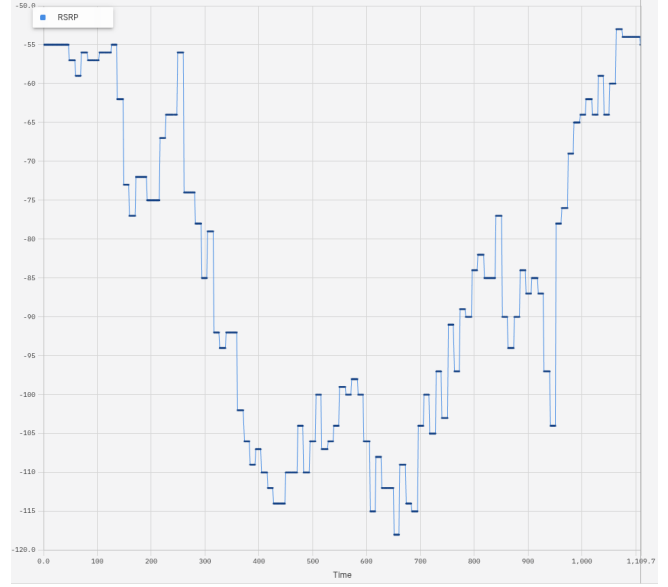


Fig. 8. The collected RSRP values during the mobile robot deployment.

is provided together with a 3D voxel map. The dataset can be summarized as follows.

- 3D Point cloud environment map as Point Cloud Data (.pcd) file of the size about 30 MB.
- Estimate position of the robot in the standard TUM format— space-separated, time-stamped robot pose consisting of three position coordinates in the world frame and four values of orientation in the world frame represented as a unit quaternion. The text file of less than 1 MB large contains about 11 thousand estimates.
- The robot traveled about 300 m long path in about 18.5 min.
- 5G measurements are stored in .json text format. The real readouts rate is about 0.66 Hz on average with the values in the range of -55 dBm to -118 dBm. Although the primary concern is time-stamped RSRP values, the recorded values also include band, sinr_value, rsrq_value, and cell_id, which can be used with multiple cells.

Measurements are localized using SLAM, as described in Section III-A, with an estimated accuracy of about 0.5 m. An overview of the 3D map with the RSRP along the robot's traveled path is depicted in Fig. 1.

In addition to the created map, robot path, and 5G measurements, LiDAR data and IMU readouts are stored in a raw MCAP dataset, as a single 43 GB file. The LiDAR scans arrive at a rate of 10 Hz, and IMU measurements at a rate of 124 Hz.

V. CONCLUSION

The presented dataset provides a realistic, accurately geo-referenced basis for studying 5G connectivity under mobility across indoor and outdoor environments. Combining robotic data acquisition with precise localization enables reproducible evaluation of spatial signal variations. It supports the

development and benchmarking of data-driven propagation models and performance analysis methods for heterogeneous 5G deployments. Although the dataset is limited to a relatively small portion of a single building, the overall methodology is applicable elsewhere. Therefore, we plan additional deployments beyond the actual signal accessibility modeling.

ACKNOWLEDGMENTS

The authors would like to thank Martin Škarytka for robot preparation and Jan Bayer for his active involvement in data collection.

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