Track 7: 5G Channel Impulse Responses

10th IPIN Competition off-site Indoor Localization, version 1.0

Maximilian Stahlke[1] Andreas Porada[1] Christopher Mutschler[1]
{firstname.lastname}@iis.fraunhofer.de

[1]Fraunhofer Institute for Integrated Circuits IIS

1 Introduction

Radio-Frequency (RF) positioning in cluttered indoor environments is challenging. As signals travel through the environment along different paths it is difficult to determine the correct time-of-arrival (TOA) of the transmitted signals. While classical TOA based positioning algorithms can achieve high localization accuracies in line-of-sight (LOS) conditions, fingerprinting methods have been used to estimate a rough position from narrow-band signals such as Wi-Fi or Bluetooth. However, with modern 5G new radio technologies, signals can be transmitted at higher bandwidths, enabling a much higher spatial resolution from which we can the extract complex propagation conditions such as absorption, reflection, diffraction and scattering [1].

To leverage the benefits of the high spatial solution we can make use of the *channel state information* (CSI). For sufficiently high bandwidths, the CSI roughly corresponds to the complex-valued *channel impulse response* (CIR). Recently, these signals have been used for positioning in different ways [2]:

- *Model Error Mitigation*: The CSI is used to classify propagation conditions like non-line-of-sight (NLOS) or to estimate time-of-flight errors caused by obstructed LOS (OLOS). This enhances classic tracking algorithms by providing additional information on the channel states [3].
- *Fingerprinting*: The propagation conditions are assumed to cause significant differences in the spatial behavior of the CSI, which can be exploited by comparing them with previously recorded data (either using the CSI or extracted features). For Machine Learning (ML) and Deep Learning (DL) approaches this constitutes a regression task [4].
- *Hybrid localization*: Fingerprinting methods are combined with classical mulilateration. As fingerprinting is only needed in NLOS dominated areas, a combination of both approaches can enhance the accuracy in mixed (LOS / NLOS) environments [5].

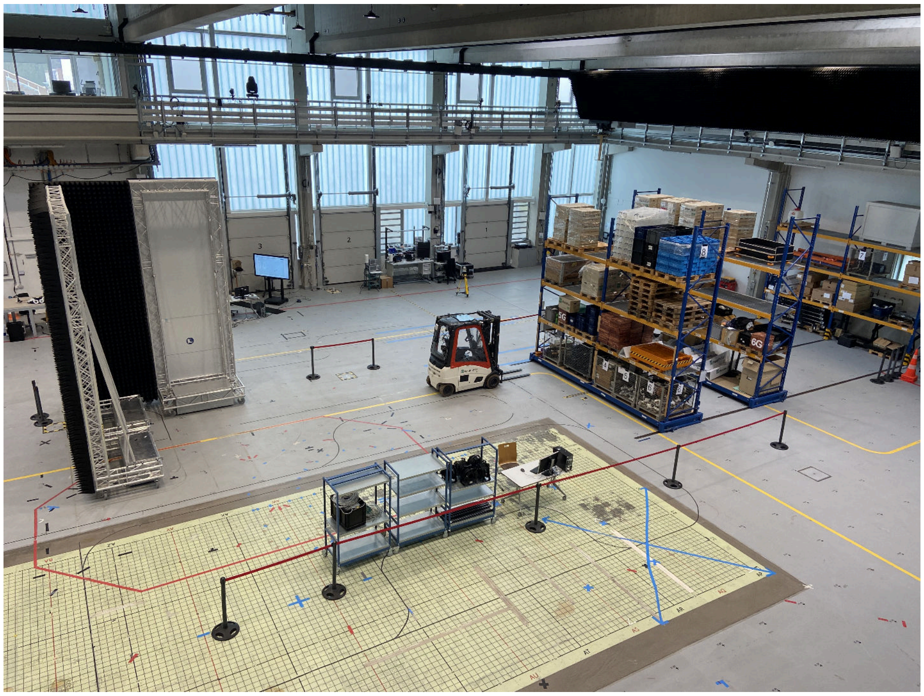

Figure 1: Image of the real world environment.

We present a dataset that contains a realistic indoor tracking scenario in an industrial setting to allow a fair comparison of practical localization solutions.

2 Challenge Objectives

While the focus of last years challenges were on UWB radio signals with 500MHz bandwidth, this year's radio system has a lower bandwidth of only 100MHz. Furthermore, the data is recorded by a smartphone carried by a person causing additional shadowing by the persons body. We recorded the data in an environment with heterogeneous radio propagation conditions as shown in Fig. 1. There are areas with NLOS for the majority of the anchors, e.g., between the shelves and close to the absorber walls, and there are more open sections with LOS to most of the anchors. The provided training data covers only the areas with dominated NLOS propagation. We therefore encourage the participants to combine both, NLOS positioning (i.e., model error mitigation or fingerprinting) and classical time-difference-of-arrival (TDOA) positioning, to achieve a overall robust localization solution.

3 Environment and Measurement Setup

The environment consist of a warehouse area of approx $1,200\text{m}^2$ with an enclosure by reflecting walls , consisting of the walls of the warehouse, including metal gates. The environment contains various metal objects, like e.g., industrial vehicles or metal shelves. Fig. 1 shows a picture of a part of the warehouse. Eight Receiving anchors are placed at the walls of the environments in different heights. The transmitter device is carried by a person at a constant height of 1.05m and regularly transmits 5G signals received by the anchors. The data is recorded by a 5G new radio platform with a bandwidth of 100MHz and a center frequency of 3.75GHz. The ground truth position of the transmitter is collected with a millimeter-accurate tracking system. The data is recorded and synchronized by an NTP server and pre-processed (corrupted datapoints are removed and RF and positioning reference data are synchronized).

4 Dataset description

The training dataset is provided as a `.csv` file. Each line of the file contains a timestamp `rec_time ([float])` and a `json` string with one instance of measurement data. The files contain the CSI and reference positions. Each data instance (i.e. `json-string`) contains:

- `rec_time ([float])`: the timestamp in s at which the CIR was received at the receiver node. (This is the ”global time index” of the tracking problem)
- `window_start_time ([float])`: timestamp in s, which indicates the start time of the window of the CIR.
- `TOA ([float])`: TOA in s, which indicates the time of the first signal arriving at the reciever. The tap within the CIR, which is identified as first path, can be determined by subtracting the window_start_time from the TOA.
- `burst_id ([int])`: the receiver time index. This can be used for synchronization. At each of the burst IDs, the transmitter (i.e., the mobile node) transmits an impulse that is received by the receivers (i.e, anchors).
- `csi_real (array[int])` and `csi_imag (array[int])`: the real and imaginary parts of the CSI as tuples. The CSI is centered around the first distinct peak and contains 128 samples each, with a sampling frequency of 184.32MHz.
- `anch_id ([string])`: the anchor id of the receiving anchor.
- The positions of the agent (i.e. the mobile tag, the transmitter) `ref_x`, `ref_y` as `float`. The reference positions are corresponding to the receiver timestamp `rec_time`.

Therefore the `.json-string` of each element has the form

```
{
    rec_time:  ...,
    window_start_time:  [...],
    TOA:   [...],
    burst_id:  ...,
    csi_real:   [...],
    csi_imag:   [...],
    anch_id:   "...",
}
```

the data can be downloaded at `https://owncloud.fraunhofer.de/index.php/s/GJ5fJDKl5xAjgID`. There are three files, the `training.csv` in the .json format, a `experimental_trial.csv` with a short trajectory in the entire environment in the .json format and an additional `.txt`-file (`anchors.txt`) containing the anchor/receiver positions is also available. It contains:

- `anch_ID [string]` the anchor IDs.
- `p_x, p_y [float]` positions of the anchors.

For each setup (i.e. the trial) the initial position is available: It is $[13.18, 18.16]$m for the experimental and $[19.33, 11.40]$m for the scoring trial.

4.1 Submission

The submission of results is done via the EvaalAPI (https://evaal.aaloa.org/evaalapi/), emulating a real-time localization setting. The general workflow for submission is as follows:

1. the user initially requests the latest data (i.e. the sensor readouts of the first 0.5 s) from the server, starting a new trial.
2. the user then estimates the position and sends it to the server. The server then advances the locally maintained time by 0.5 s and sends all sensor readouts that have occurred in this interval. This repeats until the trail ends or an error occurs.

You find details on the API and related communication in the online documentation on the website.

5 Evaluation metrics

The Euclidean distance between estimated and true results (each 2D-positions) is the main evaluation metric. Specifically, third quartile is used as a performance metric.

6 Download

You can download the training and validation datasets at `https://owncloud.fraunhofer.de/index.php/s/GJ5fJDKl5xAjgID`. Please don't hesitate contact us for any questions you might have.

References

[1] A. Molisch, "Ultra-wide-band propagation channels," *Proceedings of the IEEE*, vol. 97, pp. 353 – 371, 03 2009.

[2] S. Aditya, A. F. Molisch, and H. M. Behairy, "A survey on the impact of multipath on wideband time-of-arrival based localization," *Proceedings of the IEEE*, vol. 106, no. 7, pp. 1183–1203, 2018.

[3] H. Wymeersch, S. Maranò, W. M. Gifford, and M. Z. Win, "A machine learning approach to ranging error mitigation for uwb localization," *IEEE transactions on communications*, vol. 60, no. 6, pp. 1719–1728, 2012.

[4] A. Niitsoo, T. Edelhäußer, and C. Mutschler, "Convolutional neural networks for position estimation in tdoa-based locating systems," in *Proc. 9th Intl. Conf. Indoor Positioning and Indoor Navigation, Nantes, France*, pp. 1–8, 2018.

[5] A. C. Eyng, O. K. Rayel, E. Oroski, and J. L. Rebelatto, "Kalman filtering-aided hybrid indoor positioning system with fingerprinting and multilateration," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, (Antwerp, Belgium), IEEE, 2020.