

Track 7: 5G Channel Impulse Responses with Smartphone Sensor Information

12th IPIN Competition off-site Indoor Localization, version 1.0

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1 Introduction

Classical Radio-Frequency (RF) positioning in cluttered indoor environments is challenging, due to absorption, reflection, diffraction and scattering. However, modern algorithms, such as Fingerprinting [1], utilize those propagation effects contained in the received signals, to create a unique mapping from the radio signal to the position. Fingerprinting methods are widely 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 gain more precise position results by examining complex propagation conditions [2].

To leverage the benefits of the high spatial resolution we can make use of the channel impulse response (CIR). Due to the high bandwidth, the reflections of the environment can be identified and exploited to create highly valuable fingerprints of the environment. Machine learning methods can utilize the high dimensional CIR to learn a end-to-end regression model for fingerprinting [3].

To improve coarse localization results additional sensor information, such as inertial sensors, can be utilized as they include information about the movement of the agent. 5G enabled devices, such as smartphones, often include additional sensors, such as an accelerometer, gyroscope or magnetometer, which allows to estimate the motion of a person. By the fusion of both data sources, i.e., the position results from the fingerprinting model and the smartphone sensor information, improved localization accuracies can be achieved [4].

2 Challenge Objectives

In this year's challenge, a 5G radio system with a bandwidth of 100MHz is used as the basis. Furthermore, sensor measurements delivered from a commercial



Figure 1: Image of an example real world environment.

5G smartphone are provided. The smartphone is carried by a person within the area similar to that in Fig. 1. We recorded the data in an environment with heterogeneous radio propagation conditions. There are areas with non-line-of-sight (NLOS) for the majority of the basestations, e.g., between the shelves and close to the absorber walls, and there are more open sections with line-of-sight (LOS) to most of the basestations. This year we assume that the radio units have no time synchronization and therefore no information about time (difference) of arrival. However, fingerprinting can still provide semi-accurate positions by leveraging the patterns of multi-path propagation in the CIR. The participants are encouraged to combine these positions with dead reckoning methods, utilizing the sensor information from a smartphone, to achieve an overall robust localization solution.

3 Environment and Measurement Setup

The environment consists of a warehouse area of approximately $1,200\text{m}^2$ with an enclosure of reflecting walls, consisting of the walls of the warehouse, including metal gates. The environment contains various metal objects, like industrial vehicles or metal shelves. Fig. 1 shows an exemplary environment.

Four Receiving basestations are placed at the walls of the environment. The smartphone is carried by a person at a height of approx. 1.05m and regularly transmits 5G uplink signals received by the basestations. The data is recorded by a 5G radio platform with a bandwidth of 100MHz and a center frequency of 3.75GHz. Additionally, sensor information from the smartphone is provided, i.e., acceleration, rotation, magnetic field and orientation, with a frequency of 100Hz. The ground truth position of the transmitter is collected with a sub centimeter-accurate tracking system. The data is recorded and synchronized by an NTP server and pre-processed (all CIRs are aligned to their first signal peak).

4 Dataset description

The training dataset is provided as a .json file. Each object in the array is either *CIR* data or *sensor* data. For training and validation purpose, a second file with the reference positions is provided in the *ref_pos* format. The structure of the *CIR* data is the following:

- `time` ([float]): the timestamp in s at which the CIR was received at the receiver node.
- `cir`: Array with the CIR data from every basestation.
 - `bs_id` ([int]): the id of the basestation.
 - `cir_real` (array[int]) and `cir_imag` (array[int]): the real and imaginary parts of the CIR as tuples. The CIR is aligned by the first arriving path and contains 128 samples each, with a sampling frequency of 184.32MHz.

The structure of the *sensor* data is the following:

- `time` ([float]): timestamp in s when the sensor data was recorded.
- `acceleration` (array[float]): acceleration vector (x,y,z) in $\frac{m}{s^2}$ measured by the smartphone.
- `rotation` (array[float]): rotation data vector (x,y,z) in $\frac{rad}{s}$ measured at the gyroscope of the smartphone.
- `magnet` (array[float]): magnetic field vector (x,y,z) in μT measured by the smartphone.
- `orientation` (array[float]): orientation of the smartphone given as a quaternion.

The structure of the *ref_pos* data is the following:

- `time` ([float]): the timestamp in s at which the reference was recorded.

Listing 1: Dataformat *CIR*

```
{
  "time": ...,
  "cir": [
    {
      "bs_id": ...,
      "real": [...],
      "imag": [...],
    },
    ...
  ]
}
```

Listing 2: Dataformat *sensor*

```
{
  "time": ...,
  "acceleration": [...],
  "rotation": [...],
  "magnetic": [...],
  "orientation": [...]
}
```

Listing 3: Dataformat *ref_pos*

```
{
  "time": ...,
  "ref_pos_x": ...,
  "ref_pos_y": ...
}
```

- `ref_pos_x` ([float]), `ref_pos_y` ([float]): position of the smartphone. Only in training and validation data sets.

There are five files, the `training.json` and `training_ref.json`, `experimental_trial.json` and `experimental_trial_ref.json` with a short trajectory in the entire environment in the json format and an additional .txt-file (`basestations.txt`) containing the basestation positions is also available. It contains:

- `bs_id` [string] the basestation IDs.
- `pos_x`, `pos_y` [float] positions of the basestations.

4.1 Submission

Results can be submitted via the EvaalAPI (<https://evaal.aaloo.org/evaalapi/>). The general workflow for submission is as follows:

1. the user requests the data, where the full dataset can be downloaded at once. At this point the trial is started.
2. now, the user processes the data, estimates the positions and stores the results.
3. as the last step, the user uploads the position results at once within a certain time interval.

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 error metric, while the third quartile of the distribution of the errors is used as a performance metric.

References

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