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Client:
Thesis: M.Sc.

Applicability of Machine Learning for Time of Arrival Estimation

Keywords: Time Series, Time of Flight, Time of Arrival, Time Difference of Arrival, Time or Frequency Domain, Machine Learning, Deep Learning, Localization.

Motivation. Time of arrival (ToA) based radio systems are widely used for indoor localization achieving accuracies in the centimeter range. However, their positioning performance is restricted due to bandwidth limitations and challenging propagation conditions. Complex environments like production lines can deteriorate the positioning performance dramatically. Absorptions, reflections, and scattering cause wrong ToA estimations, which lead to localization errors. Thus, data-driven approaches have been investigated to mitigate the ToA estimation errors considering environmental specific properties. Often the channel impulse response (CIR) is used, as the CIR contains rich spatial information which help localization algorithms to improve the positioning accuracy by, e.g., for obstructed- or none-line-of-sight (O/NLoS) identification [3], error mitigation [1] or ToA estimation [2]. However, data-driven approaches often have a poor generalization towards data-distribution shifts (in this case changed or new environments), which cause wrong predictions. Also ambiguities in the data, caused, e.g., due to bandwidth limitations and NLoS impairments, harden the generalization of ToA estimation.

To compensate for these challenges, transfer learning helps fine-tune a pre-trained model from a given environment to changes or a new environment. However, transfer learning is expensive w.r.t. the effort involved in data acquisition in the real world. For example, Feigl et al. [2] investigated an approach to simulate training data of a given environment and return ToA predictions directly on real data or fine-tune the model on real data to provide the most accurate data possible. However, they indicated that further research is important examining: "*How to simulate ToA data in an OLoS or NLoS scene that is similar to the real world*", "*How to collect real-world data to use a pre-trained Fine-tuning the model*", "*How to generalize in OLoS and NLoS scenes*". As it is technically difficult to collect data covering OLoS and LoS situations, it is impossible to answer these questions. If we exploit the time difference of arrival (TDoA) however, determining from both the simulation and the real data, we may have the opportunity to refine and generalize the AI-based TDoA estimation.

Idea. The core idea of this thesis is to investigate: "*How to best determine realistic TDoA measurements on simulated data from* QUADRIGA*?*", "*How to process these TDoAs with AI to implicitly denoise them and derive correct relative first direct paths of arrival (FDPOAs)?*" and "*How to apply this approach to real-world applications*". In addition, the student may also define other features or consolidate the definition of the existing ones: IQ-Ratio, Cplx-Area, DiffLeft, DiffRight. These should be evaluated and evaluated which features make the best contribution to the accuracy of the relative FDPOA determination. Optionally, different KF estimators can be evaluated (KF-Early, Subtract SINC or "power window only).

Overall goals

Classic channel parameter estimators (here the time-of-arrival, ToA, of a synchronized radio system), such as threshold-, inflection-point- or super-resolution-based methods, have great difficulty estimating the correct ToA of radio signals if the radio propagation is disturbed by multipath. As part of a qualification thesis, the student will examine the processing chain of a

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channel parameter estimator using data-driven methods. And evaluate the absolute positioning capabilities of AI methods on TDoA input w.r.t. to a specific constant receiver.

- Acquisition of noisy real channel impulse responses are collected;
- Configurations of the QUADRIGA simulator are derived from there;
- Synthetic channel impulse responses are generated using this simulator;
- A suitable AI method is (optimized) trained on this synthetic and real data;
- The trained channel estimators are applied on different antenna units for parameter estimation and position estimation e.g. by multilateration;
- The evaluation mechanisms of the state-of-the-art methods are being improved and possible effects on the 3GPP standard are being examined.

Timetable (6 months, in person weeks [PW])

4PW Literature and patent research; Familiarization with relevant work on the subject areas;

10PW Methodological work: adaptation of the individual components to the state-of-the-art methods and advances to the state-of-the-art based on recent deep learning methods;

4PW Evaluation and real-world demonstration;

6PW Transcript.

Expected results and scientific contributions

- AI-based TDoA estimator that generalizes to changes and new environments;
- The same method, that purely works on simulations (best case);
- The same method, that uses fine tuning on few noisy real world TDoAs;
- A demonstrator that shows the applicability and generalizability of the framework on a simple indoor environment;
- The demonstrator will show that it lowers the effort of training data acquisition.

References

[1] Simone Angarano, Vittorio Mazzia, Francesco Salvetti, Giovanni Fantin, and Marcello Chiaberge. Robust ultra-wideband range error mitigation with deep learning at the edge. *Engineering Applications of Artificial Intelligence*, 102:104278, 2021.

[2] Tobias Feigl, Ernst Eberlein, Sebastian Kram, and Christopher Mutschler. Robust toa-estimation using convolutional neural networks on randomized channel models. In *Intl. Conf. on Indoor Positioning and Indoor Navigation (IPIN)*, pages 1–8. IEEE, 2020.

[3] Maximilian Stahlke, Sebastian Kram, Christopher Mutschler, and Thomas Mahr. Nlos detection using uwb channel impulse responses and convolutional neural networks. In *Intl. Conf. on Localization and GNSS (ICL-GNSS)*, pages 1–6. IEEE, 2020.