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Thesis:	Bachelor or Masters Thesis

(Un)Supervised Jammer Localization on Multivariate Time Series of GNSS Signals

Keywords: Jamming, GNSS, Time Series, Time or Frequency Domain, Machine Learning, Deep Learning, Localization, conditional VAE, channel charting, Fingerprinting.

Motivation. Jamming threats are increasing in the global navigation satellite system (GNSS) bands. The main cause of GPS failures is interference signals in the GPS frequency bands. An interfering signal can typically be divided into self-made or channel-based. Self-made interference is subdivided into (1) intentional, e.g., jamming or spoofing, or (2) unintentional, e.g., interference produced by other systems such as inter-modulation products or radio resource allocation. In contrast, channel-based interference includes phenomena such as multipath, atmospheric scintillation or fading. Jamming can then be defined as intentional (narrowband) interference in the wireless bands of interest, with received powers that are several orders of magnitude higher than the received useful powers, in this case the powers of the GNSS signals. The large differences in received power between the jammers and the GNSS signals are due to the fact that the jammers are typically placed on or near the surface of the earth. Thus, the path-loss attenuation of the GNSS signals is significantly higher than that of the jammer signals.

Related work.
There are several ways to deal with jamming, such as: detection [1, 2, 3], mitigation [1, 4, 5, 6], localization [2, 7] or classification [8, 9, 10]. However, very little (research) effort has been devoted to the localization of the jammer. There are several main categories of jammers: (1) amplitude modulated, (2) chirp, (3) frequency modulated, (4) pulse or range finder-like devices, (5) narrowband and (6) broadband jammers, which are typically very difficult to detect and thus to localize, since the signal properties in the time and frequency domains are very similar in the presence and absence of jammers. State-of-the-art jammer localization approaches apply detection, attenuation, and either TDoA or PDoA or a mixture thereof to the time and / or frequency space of GNSS signals to locate a jammer. Although this mechanics has been shown to be optimal jammer locators w.r.t. to high JNRs and line of sight conditions, we claim that both supervised fingerprinting [12] and unsupervised channel charting [11] machine and deep learning methods have shown the highest accuracies and robustness recently w.r.t. (non) line of sight, even at very low SNRs in the field of CSI-based localization on ultra-broadband signals.

Overall goal. This thesis will examine and adapt, modern data-driven localization methods to the problem at hand. The models will be calibrated on the data from both perspectives: per specific dataset and, in general, on all datasets. The uncertainty of the confidence values will be examined. A final live demonstration shows the practical applicability of the pipeline.

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.

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6PW Transcript.

Expected results and scientific contributions.

- Jammer localization should be treated as an (un)supervised localization problem based on the time and / or frequency domain signals and / or characteristics at the GNSS receiver, e.g., supervised - fingerprinting - end-to-end [12]; and unsupervised - constrained latent space interpretation with a conditional Variational Auto Encoder (VAE) or siamese network [11];
- The efficiency of the methods should be evaluated based on the most modern methods for localization [11, 12], their adaptation to the problem at hand and an optional optimization, to finally surpass the state-of-the-art w.r.t. the research community of jammer localization (TDoA and PDoA) [1, 6];
- Specific and general models are intended for different types of GNSS sensors and their individual data streams w.r.t. localization accuracy, MAE, MSE, RMSE, CEP scores, and reliability (uncertainty and model calibration) for a variety of carrier-to-noise ratios (C/N0) and jammer-to-signal ratio (JSR) are examined.
- Modular processing pipeline that consists of, e.g., an TDoA, PDoA, MUSIC, [**?**, **?**] deep learning-based fingerprinting [12], and unsupervised conditional VAE (channel charting) [11].
- A localization pipeline that is real-world applicable and replaces state-of-the-art jammer locators. The real-world applicability will be proven by a live demonstrator.
- The pipeline is to be implemented in Python with the support of pytorch, scipy, and scikit.learn.
- The model uncertainty should be examined in relation to Monte Carlo dropout masks, ensembles, Bayesian inference or SWAG / Laplace.

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