Student:	..
Supervisor/s:	Tobias Feigl
Client:	..
Thesis:	Bachelor or Masters Thesis

Novelty and Anomaly Detection in Multivariate Time Series of Jammed GNSS Signals

Keywords: Jamming, GNSS, Time Series, Time or Frequency Domain, Machine Learning, Deep Learning, Novelty and Anomaly Detection, Out-of-Distribution Detection.

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 jamming detection algorithms. 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, since the signal properties in the time and frequency domains are very similar in the presence and absence of jammers. Recent research is using machine learning methods to detect jammers, but it is only looking at simple machine learning algorithms that may not be complex enough to cover all of the nonlinearities in these signals and require detailed feature analysis. And they only study synthetic signals, which leaves the question open of how their method works in the real world with a variety of signals from different sensors. [**?**, **?**, **?**]

Overall goal. The thesis should examine modern detection algorithms such as (variational) autoencoder (VAE), a combination of generative adverserial network (GAN) and VAE, and similar state-of-the-art methods, and adapt them to the problem at hand. The models should be calibrated on the data from both perspectives: per specific dataset and in general on all datasets. The uncertainty of the confidence values should also be examined, e.g., with ensembles. A live demonstration will show 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: detector adaptation (add uncertainty estimation functionalities), (un)supervised training schemes, and architecture optimization.
- 4PW Evaluation and real-world demonstration.
- 6PW Transcript.

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Expected results and scientific contributions.

- Jammer detection should be treated as an (un)supervised detection problem based on the time and / or frequency domain signals and / or characteristics at the GNSS receiver;
- The efficiency of the methods should be evaluated based on the most modern methods for novelty and anomaly detection or out of distribution detection [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 detection;
- Specific and general models are intended for different types of GNSS sensors and their individual data streams w.r.t. detection accuracy, F-β scores, reliability (uncertainty and model calibration) for a variety of carrier-to-noise ratios (C/N0) and jammer-to-signal ratio (JSR) are examined.
- Based on the work by Niu et al. [12], the modular processing pipeline is intended to e.g., consist of VAE, GAN, mixture of both and classic and specific neural network detectors.
- A practical detection pipeline should replace the most modern detectors. The practicability is to 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 w.r.t. Monte Carlo dropout masks, ensembles, Bayesian inference or SWAG / Laplace.

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