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Thesis:	Bachelor or Masters Thesis

Multivariate Time Series Classification of Jammers in GNSS Signals

Keywords: Jamming, GNSS, Time Series, Time or Frequency Domain, Machine Learning, Deep Learning, Classification.

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 classification 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 or to be classified, since the signal properties in the time and frequency domains are very similar in the presence and absence of jammers.

Overall goal. The thesis will examine and adapt, modern classifiers to the problem at hand. The models will be calibrated on the data from both perspectives: per sensor- and application-specific dataset and in general on all datasets. The uncertainty of the confidence values will be also examined. A final live demonstration will show the practical applicability of the pipelines.

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

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

10PW Methodological work: classifier adaptation (add uncertainty estimation functionalities), (un)supervised training schemes, and architecture optimization.

4PW Evaluation and real-world demonstration.

6PW Transcript.

Expected results and scientific contributions.

- Jammer classification should be treated as an (un)supervised classification 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 classification [11], 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 classification;
- Specific and general models are intended for different types of GNSS sensors and their individual data streams w.r.t. classification 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 Ruiz et al. [11], the modular processing pipeline is intended to e.g., consist of a dynamic time warping, COTE and specific neural network classifiers.
- A practical classification pipeline should replace the most modern classifiers. 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.
- A model calibration should be investigated based on a sequential logistic regression.
- The model calibration and uncertainty should be examined in relation to Monte Carlo dropout masks, ensembles, Bayesian inference or SWAG / Laplace.

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