Research Avenues for GNSS Interference Classification Robustness: Domain Adaptation, Continual Learning & Federated Learning

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Abstract. Jamming devices present a significant risk by disrupting signals from the Global Navigation Satellite System (GNSS), compromising the reliability of accurate positioning. The detection of anomalies within frequency snapshots is crucial for effectively mitigating such interferences. The capacity to adapt to diverse, unforeseen interference characteristics is essential for ensuring the reliability of GNSS in practical applications. Our proposed GNSS dataset, recorded along a highway, encompasses various research challenges, including adaptation to novel interference characteristics, change in environmental conditions, and variances in GNSS receiver stations. These obstacles prompt exploration into various research directions such as transfer learning, domain adaptation, continual learning, and few-shot learning. Furthermore, real-world applications require federated learning methods for orchestrating ML models in a privacy-preserving manner. This paper elaborates on the associated challenges and outlines potential research inquiries.

Keywords: Global Navigation Satellite System · Interference Classification · Domain Adaptation · Continual Learning · Federated Learning.

1 Interference Classification in GNSS Snapshots

Introduction. Anomaly detection entails the identification of deviations within data patterns from the expected norm. In the context of GNSS-based applications [6], the detection of interference assumes a pivotal role. The disruption of GNSS receivers' localization accuracy occurs due to interference signals from jammers. Significantly, this issue has intensified in recent years due to the increased prevalence of cost-effective and accessible jamming devices [4]. Such jamming attacks yield severe consequences, including collisions involving self-driving cars [1] or disruptions in airplane GPS systems [2]. Consequently, the detection and classification of potential interference signals are imperative [3]. Both classical and ML methods have demonstrated efficacy in detecting and classifying interference. However, the unpredictable emergence of novel, "undetected" jammer types mandates rapid model adaptation. The objective is to develop ML models that exhibit resilience against diverse jammer types, interference characteristics, variations in antennas, environmental fluctuations, changes in location, and disparate receiver stations. Next, we provide a brief overview of a dataset facilitating the analysis of ML models robustness. Furthermore, we delineate the challenges and outline potential experiments. These challenges require the development of robust ML models characterized by predictability and reliability. Hence, evaluation of uncertainty quantification techniques [10] assumes high importance. The imperative to adapt to unforeseen jammer types and emerging interference characteristics, opens research avenues for methodologies such as representation learning [5], transfer learning, domain adaptation [12], continual learning (CL) [7,9], few-shot learning (FSL) [5,8], and federated learning [11].

GNSS-based Dataset. The GNSS-based dataset[1], proposed by Ott et al. [5], contains short, wideband snapshots in both E1 and E6 GNSS bands. The dataset was captured at a bridge over a highway. The setup records 20 ms raw IQ (inphase and quadrature-phase) snapshots. Figure 1 shows exemplary snapshots of the spectrogram (the x-axis shows the time in ms and the y-axis shows the frequency in MHz). Manual labeling has resulted in 11 classes: none, chirp, pulsed, noise, tone, multitone, etc. The dataset's imbalance of 197,574 samples for non-interference classes and between 9 to 79 samples per interference class emphasizes the under-representation of positive class labels.

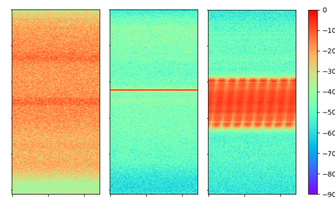

Fig. 1: Exemplary spectrograms without (1^{st}) and with (2^{nd} and 3^{rd}) interference.

Challenges & Research Avenues. To enhance the robustness of positioning systems by mitigating interferences, it is imperative to initially detect and reliably classify these interferences. However, achieving a dependable classification is impeded by several factors: (1) The presence of a multitude of potential (hardware) jammer types, each exhibiting distinct interference patterns as illustrated in Figure 1. (2) Variations in the jammers' frequency, bandwidth, and signal-to-noise ratio, which directly influence the interference patterns. Conducting a feature analysis is crucial for identifying and emphasizing the most significant extracted features. (3) Despite intentional jammers typically being constructed as in-band interferers, numerous unintentional sources of interference contribute to noise in the spectrograms. Employing data augmentation techniques can boost the resilience of ML models. (4) Environmental changes, such as fluctuations in weather conditions (e.g., temperature) or alterations in multi-path scenarios, necessitate the utilization of representation learning, transfer learning, and domain adaptation methods. These changes introduce shift in feature distributions between source and target domain samples. (5) Difficulties arise in transferring models across diverse hardware setups, including low-cost, medium-end, and high-end sensors, smartphone data, and various antennas. CL and FSL methods enable adaptation to novel data types. (6) Effectively classifying and promptly adapting to interferences across different locations requires orchestrating ML

[1] Dataset available at: https://gitlab.cc-asp.fraunhofer.de/darcy_gnss/FIOT_highway

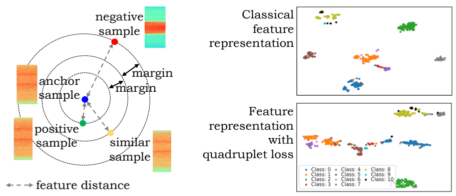

Fig. 2: Representation learning.

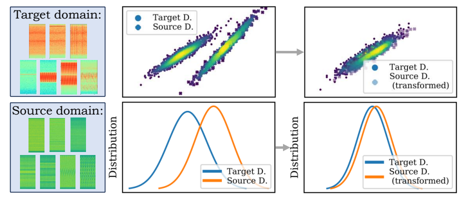

Fig. 3: Domain adaptation.

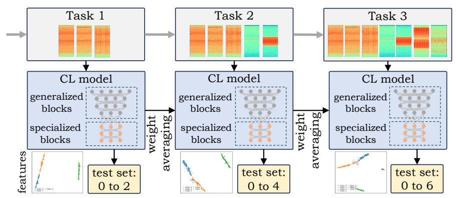

Fig. 4: Continual & few-shot learning.

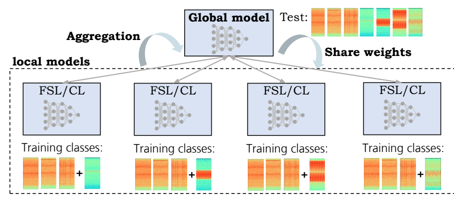

Fig. 5: Federated learning.

models by exchanging (sub-)information of new jammers. Federated learning leverages CL or FSL to adjust to unfamiliar interference classes and facilitates weight sharing through an aggregation process over a global (central) ML model.

2 Machine Learning Research

These challenges presented by real-world scenarios offer research opportunities spanning diverse trajectories that captivate both the ECML and wireless communications community. Subsequently, we provide four potential research directions.

Feature Analysis & Representation Learning. By conducting a feature importance analysis, it becomes possible to select pertinent features to enhance the model robustness, e.g., evaluated on GNSS crowd-sourcing localization [6]. By the utilization of representation learning techniques, the model can acquire more generalized features, and hence, achieves a representation characterized by continuous transitions (see Figure 2) – achieved through the utilization of pairwise learning such as triplet or quadruplet loss functions [5].

Domain Adaptation aims to minimize the discrepancy of feature embeddings between the source and target domains (see Figure 3), resulting in feature distributions with smaller distance [12]. Such alignment is imperative for accommodating snapshots acquired from diverse sensor stations. A connected research topic pertains to representation learning.

Continual & Few-shot Learning. CL [9] and FSL [8] denote the capability to sequentially learn consecutive tasks without forgetting how to perform previously trained tasks. In the context of interference classification, such methods are imperative for the adaptation to novel jammer types [5,7] (see Figure 4), including research into optimal strategies for selecting prior task samples and the dynamic configuration of architectures, exemplified by the integration of generalized and specialized blocks.

Federated Learning. By orchestrating ML models across diverse locations and facilitating the exchange of data/information concerning novel jammer types, the models' weights can be updated through an aggregation step (see Figure 5) [11]. The related research topics encompass the optimization of the aggregation step, the reduction of model parameters to mitigate data transmission volumes, and the implementation of anonymization techniques on model attributes to uphold privacy within federated learning.

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Disclosure of Interests. The authors have no competing interests to declare.

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