LARGE: AI-Enabled Spectrum Coexistence between Active Communications and Passive Radio Services: Fundamentals, Testbed and Data

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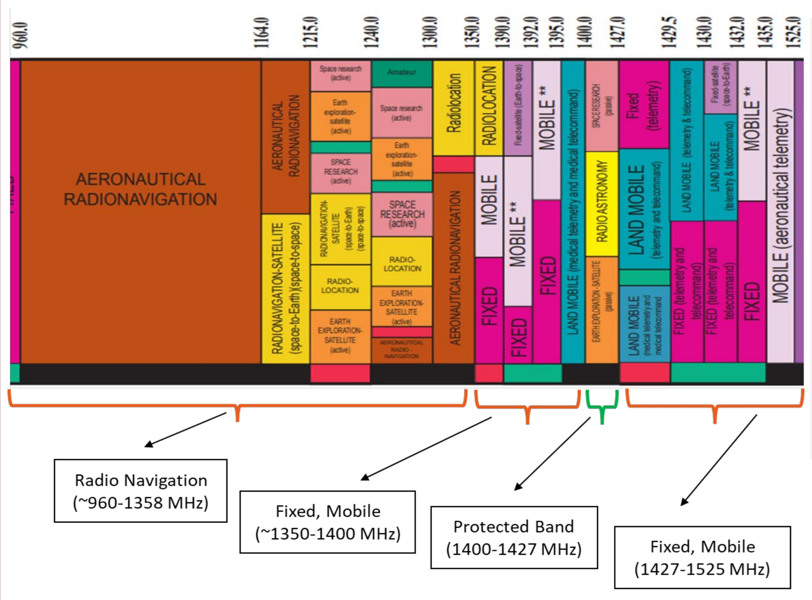
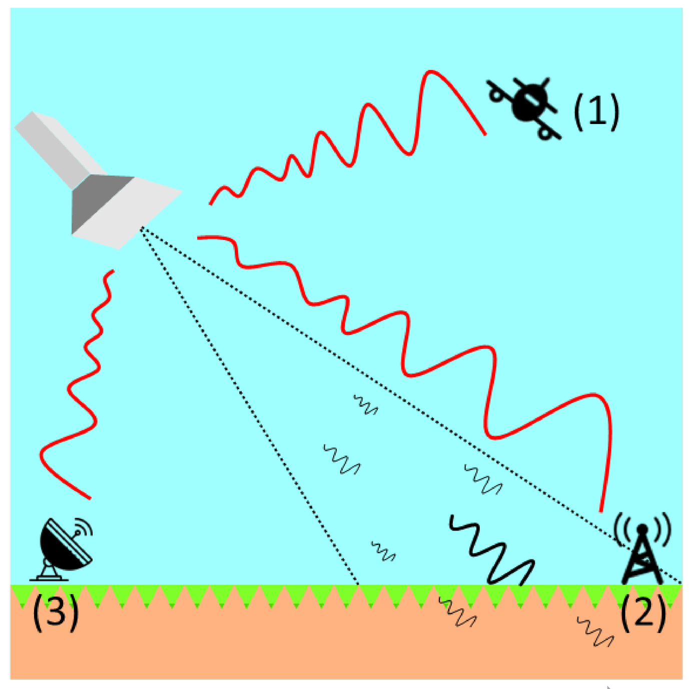
Project at a Glance



- Radio astronomy (RA), remote sensing (RS) and other passive sensing services are indispensable in modern society
- Active wireless technologies such as IoT, UAVs and 5G wireless networks are driving advances in key sectors such as healthcare, manufacturing, defense, and transportation

The growth of active wireless systems often increases radio frequency interference (RFI) experience by passive sensors



This needs research on active and passive spectrum coexistence

Task 1 (PHY-APP Layer)

1.1 AI-Enabled RFI detection and mitigation

1.2 Sparsity-based RFI detection and mitigation utilizing existing datasets from SMAP and UWBRAD

Task 2 (MAC-PHY Layer)

2.1 Sparse radio frames by wireless channel virtualization

2.2 Deep Reinforcement learning for channel mapping

2.3 AI-based Active transmission optimization

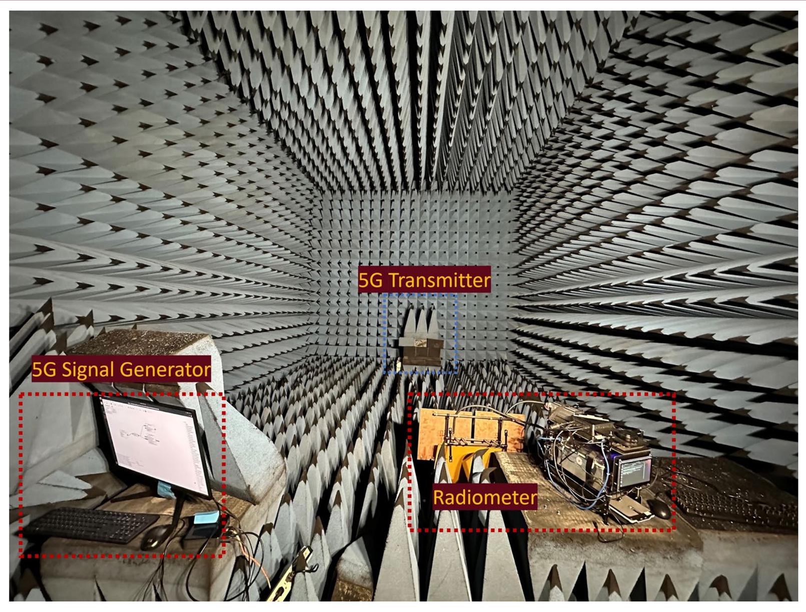
Task 3: Testbed

3.1 Ground and aerial system prototyping

3.2 Deployment of and installation of drone-based L-band radiometer

3.3 System emulator

Testbed Preparation



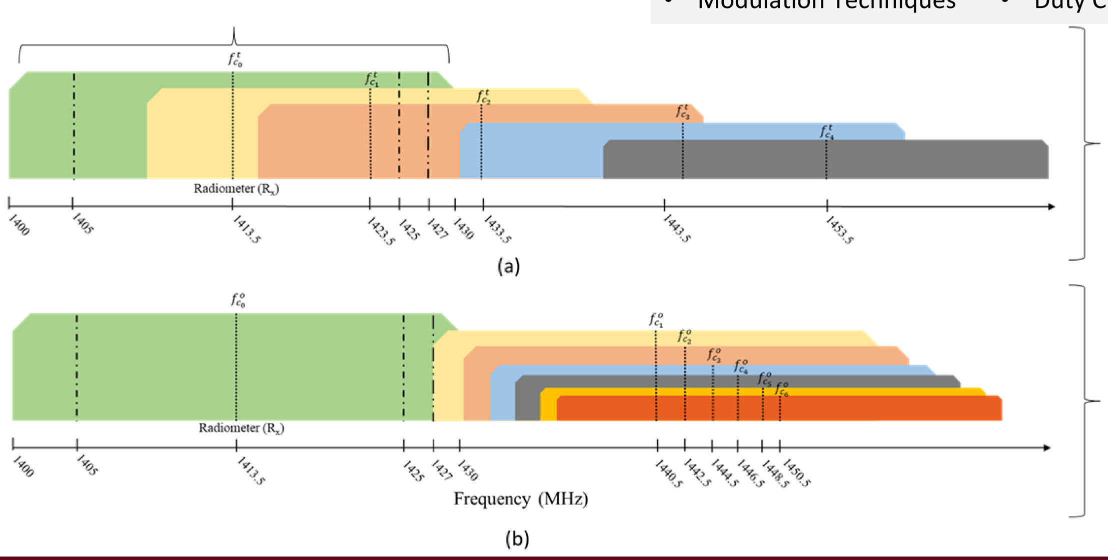
- Currently there is no publicly available dataset for active-passive co-existence research
- We have developed an open dataset and accompanying processing scripts for both **transmitted 5G samples** and **radiometer measurements**
  - SDR-based digital processing unit enables acquisition of raw IQ samples at the radiometer
  - A customizable 5G NR system enables transmitting various wireless communication signals

Experimental Scenario

In Band: 5G waveforms were intentionally propagated within the operational bandwidth of the radiometer (1400-1427 MHz).

Independent Variables in Experiment Campaign:

- Transmission Bands
- Power Gains
- Modulation Techniques
- Resource Block Group Allocations
- Duty Cycles

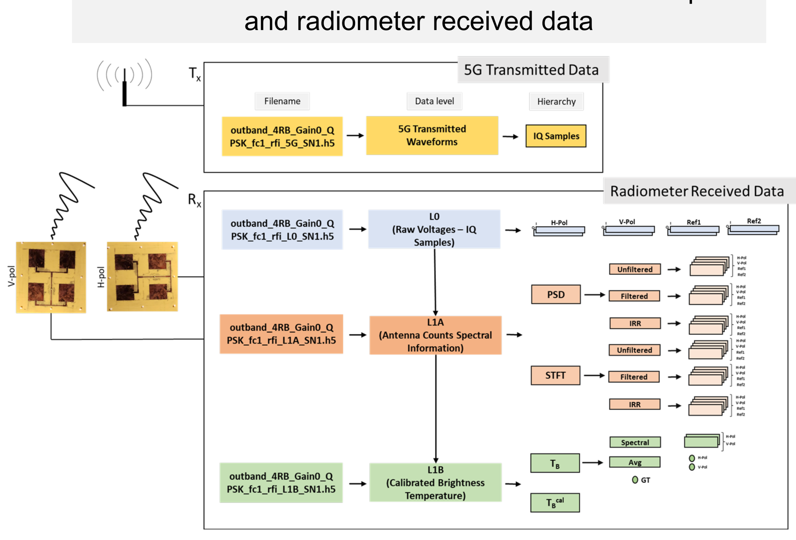


Transition Band: The center frequency of transmitted signals are shifted with 10 MHz step size spanning from 1423.5 MHz to 1453.5 MHz.

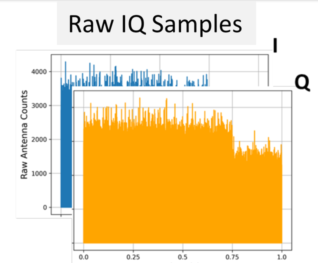
Out-Of-Band: Transmitted signals are outside the operating bandwidth of the radiometer.

Open Source Dataset

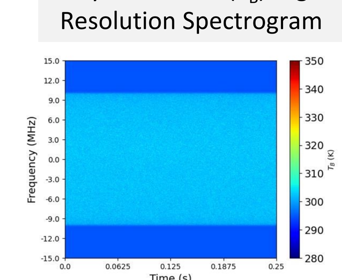
Dataset file structure for both transmitted 5G samples and radiometer received data



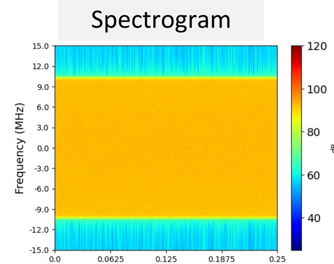
Raw IQ Samples



Fully Calibrated (T_B) High-Resolution Spectrogram



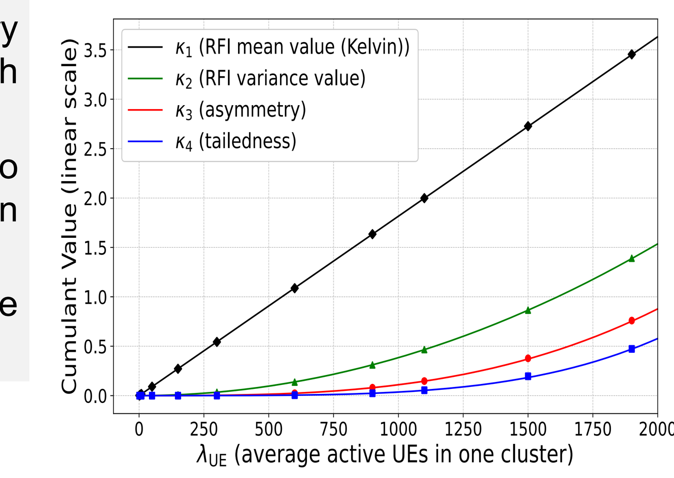
Antenna Counts Spectrogram

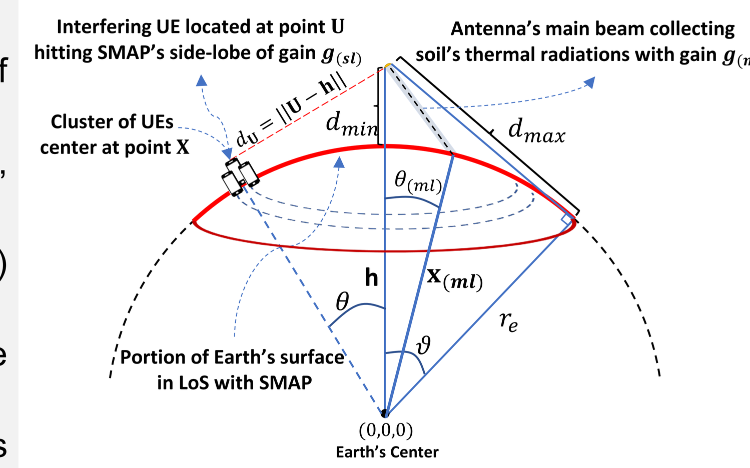


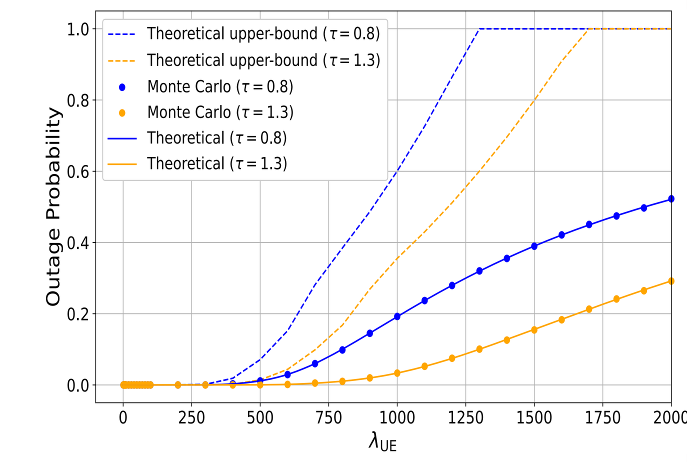
Dataset and Processing Scripts Available [GitHub Link]

Aggregate RFI Analysis using Stochastic Geometry

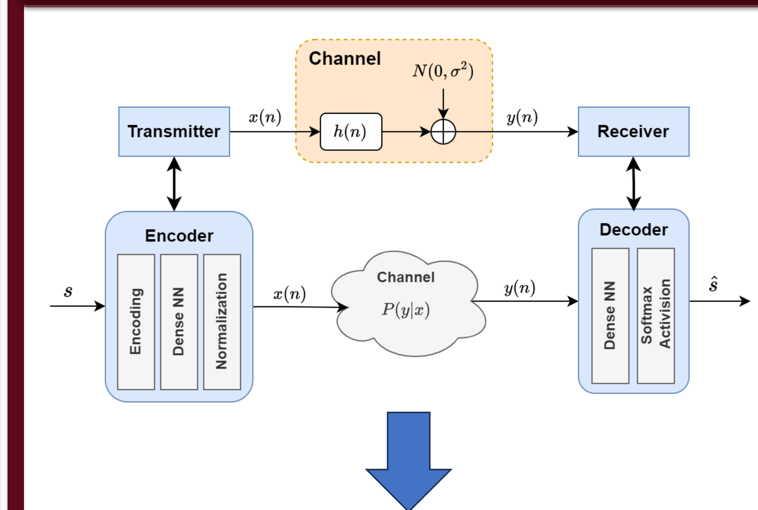
- **Goal:** Model aggregate RFI induced on a space-borne passive Remote Sensing (RS) satellite from a large-scale terrestrial NextG network
- Use a **Poisson Cluster Process** to model the distribution of cellular User Equipment (UEs)
  - Each cluster represents a dense urban area
- Use shadowed Rician fading (SRF) to model the Earth-space channel
- Derive the **characteristic function** of aggregate RFI and its **statistical properties**
  - Cumulants, average, variance, skewness, and kurtosis.
- Analyze the Sensing Outage Probability (SOP) at the RS satellite: $SOP(\tau) = P(|T - E[T]| > \tau)$
  - T denotes the RFI brightness temperature and $E[T]$ denotes its expected value
  - $E[T]$ is used to correct the RS satellite's RFI contaminated measurements
  - τ = 1.3 Kelvin for NASA's SMAP mission
- $\lambda_c = 1$ cluster (dense urban area) every 500,000 km^2. 50 clusters on Earth exposed to the satellite on average.
- $\lambda_{UE} \in [0, 2000]$ UEs per cluster. Up to 100,000 UEs are exposed to SMAP on average.
- $g_{(sl)} = -15$ dBi (extremely low side-lobe gain of SMAP's antenna)



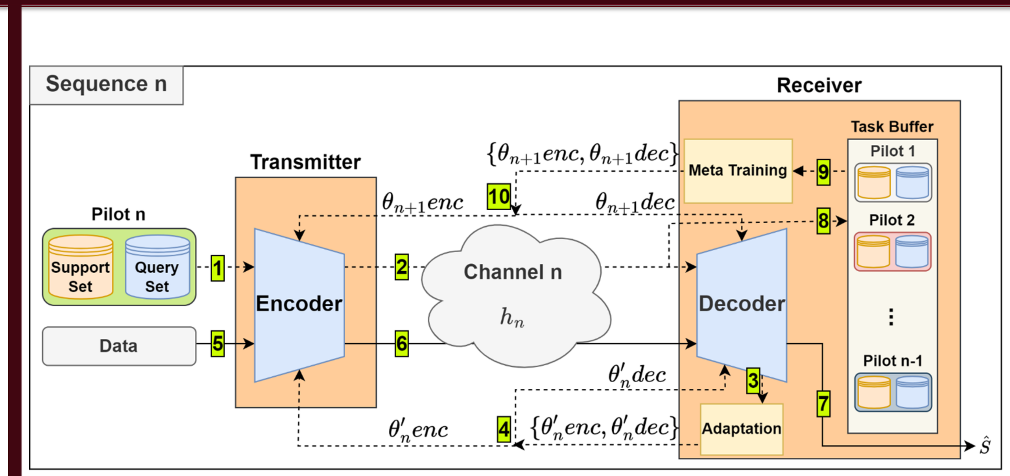


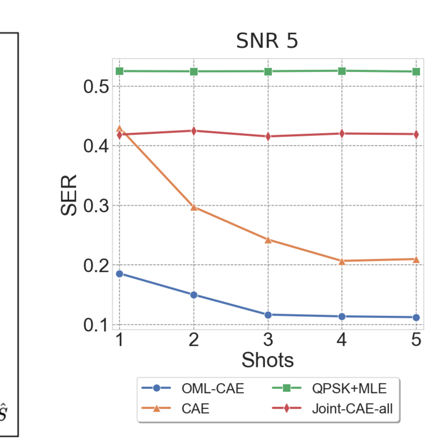


Adaptive Channel Autoencoder for Dynamic End-to-end Physical Layer Optimization



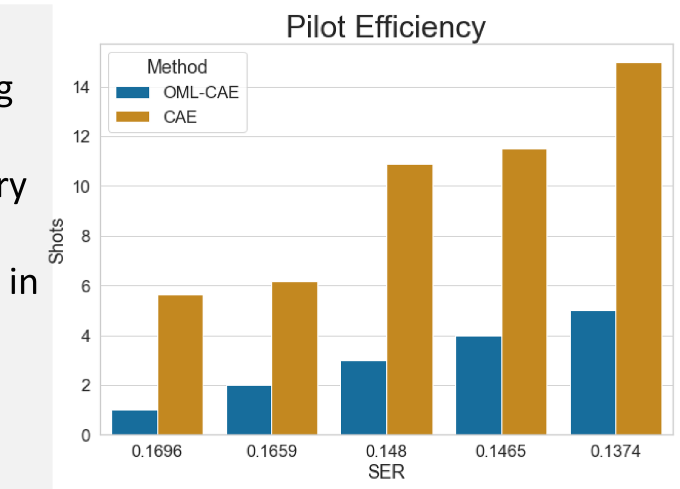
- CAE designs an optimized modulation scheme for a particular fading channel.
- The same solution can not be applied for all channels.
- CAEs have to be retrained for a new channel realization.
- Retraining requires computation resources and time.



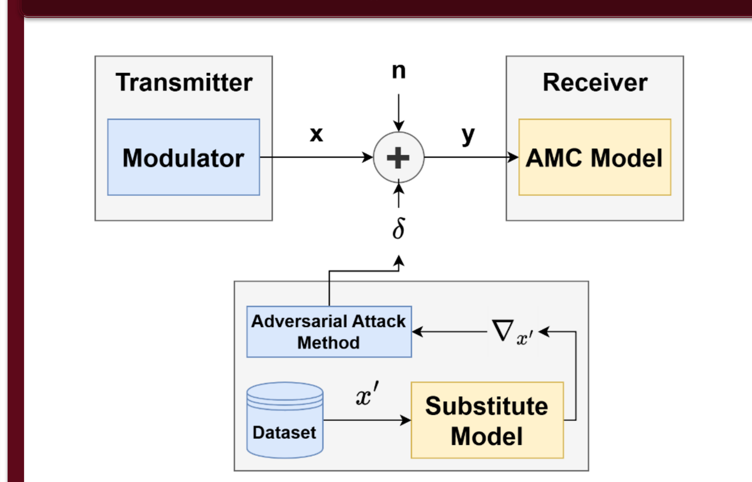


Solution: Online meta-learning CAE

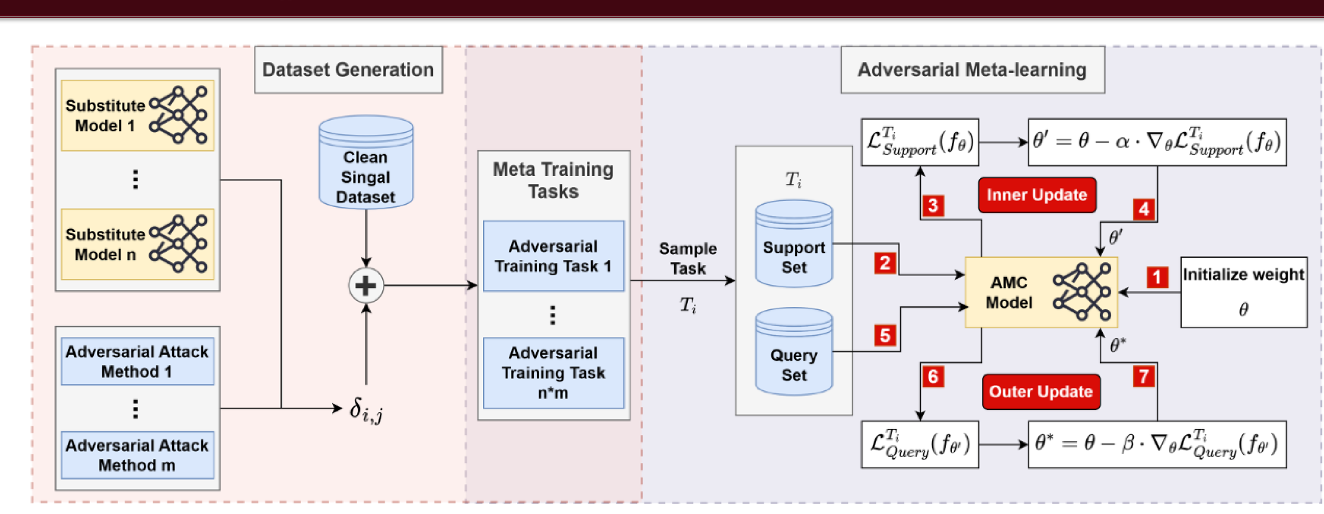
- Transmit a few pilot samples per fading channel realization.
- Use these samples as support and query sets for meta-learning.
- OML-CAE leverages accumulated tasks in a buffer for meta-training with MAML.
- MAML updates CAE initialization, then fine-tunes on current support set to obtain optimized weights.



Adaptive Adversarial Training for Modulation Classification



- Automatic modulation classification (AMC) models are vulnerable to adversarial attacks.
- Interference can exploit adversarial attacks (FGSM, PGD, CW, MIM) to fool the model.
- Adversarial perturbations are small input changes that greatly reduce accuracy.
- Adversarial training improves robustness but cannot cover infinite perturbations.
- In practice, AMC must handle unknown adversarial perturbations.



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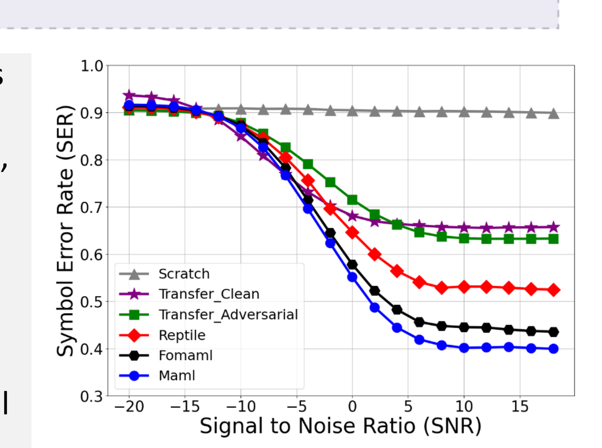

List of Publications

1. A. M. Alam, M. M. Farhad, W. Al-Qwider, A. Owfi, M. Koosha, N. Mastronarde, F. Afghah, V. Marojevic, M. Kurum, A. C. Gurbuz, "A Physical Testbed and Open Dataset for Passive Sensing and Wireless Communication Spectrum Co-Existence," in IEEE Access. [Submitted]
2. Ahmed Manavi Alam, Md Mehedi Farhad, Walaa Al-Qwider, Ali Owfi, Mohammad Koosha, Nicholas Mastronarde, Fatemeh Afghah, Vuk Marojevic, Mehmet Kurum, Ali Gurbuz, March 31, 2024, "Dataset for Spectrum Coexistence in Passive Sensing and Wireless Communication", IEEE Dataport, doi: https://dx.doi.org/10.21227/968t-td34. **[Public Dataset]**
3. A. M. Alam, M. M. Farhad, M. Kurum and A. Gurbuz, "An Advanced Testbed for Passive/Active Coexistence Research: A Comprehensive Framework for RFI Detection, Mitigation, and Calibration," 2024 United States National Committee of URSI National Radio Science Meeting (USNC-URSI NRSM), Boulder, CO, USA, 2024, pp. 280-280, doi: 10.23919/USNC-URSINRSM60317.2024.10464436.
4. A. M. Alam, M. Kurum, M. Ogut and A. C. Gurbuz, "Microwave Radiometer Calibration Using Deep Learning With Reduced Reference Information and 2-D Spectral Features," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 748-765, 2024, doi: 10.1109/JSTARS.2023.3333268.
5. W. Al-Qwider, A. M. Alam, M. Mehedi Farhad, M. Kurum, A. C. Gurbuz and V. Marojevic, "Software Radio Testbed for 5G and L-Band Radiometer Coexistence Research," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 596-599, doi: 10.1109/IGARSS52108.2023.10283002.
6. M. M. Farhad, S. Biswas, A. M. Alam, A. C. Gurbuz and M. Kurum, "SDR Based Agile Radiometer with Onboard RFI Processing on a Small UAS," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 4368-4371, doi: 10.1109/IGARSS52108.2023.10282140.
7. A. M. Alam, M. Kurum, and A. C. Gurbuz, "Radio Frequency Interference Detection for SMAP Radiometer Using Convolutional Neural Networks," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 10099-10112, 2022.
8. A. M. Alam, A. C. Gurbuz, and M. Kurum, "SMAP Radiometer RFI Prediction with Deep Learning using Antenna Counts," *2022 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, Kuala Lumpur, Malaysia, 2022, pp. 8016-8019.
9. M. M. Farhad, A. M. Alam, S. Biswas, M. A. S. Rafi, A. C. Gurbuz and M. Kurum, "SDR-Based Dual Polarized L-Band Microwave Radiometer Operating from Small UAS Platforms," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, doi: 10.1109/JSTARS.2024.3394054.
10. Walaa H Alqwider, Ajaya Dahal, and Vuk Marojevic, "Software Radio with MATLAB Toolbox for 5G NR Waveform Generation", *Proc. IEEE DCOSS 2022 - Test and Evaluation of Programmable Networks (TEPN) 2022 workshop*, Marina Del Rey, Los Angeles, CA, US, May 2022.
11. M. Koosha and N. Mastronarde, "Opportunistic Temporal Spectrum Coexistence of Passive Radiometry and Active Wireless Networks," *2022 IEEE Western New York Image and Signal Processing Workshop (WNYISPW)*, Rochester, NY, USA, 2022, pp. 1-4.
12. M. Koosha and N. Mastronarde, "Minimizing estimation error variance using a weighted sum of samples from the soil moisture active passive (SMAP) satellite", *2023 IEEE International Geoscience and Remote Sensing Symposium*, July 2023.
13. Koosha, Mohammad, and Nicholas Mastronarde. "Spectrum Coexistence of Satellite-borne Passive Radiometry and Terrestrial Next-G Networks." *arXiv preprint arXiv:2402.08002* (2024).
14. A. Owfi, F. Afghah, and J. Ashdown, "Meta-Learning for Wireless Interference Identification", *IEEE Wireless Communications and Networking Conference (WCNC)*, 2023.
15. A. Owfi and F. Afghah, "Autoencoder-Based Radio Frequency Interference Mitigation for SMAP Passive Radiometer," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 6783-6786, doi: 10.1109/IGARSS52108.2023.10281939.
16. A. Owfi, J. Ashdown, K Turck, and F. Afghah. "Online Meta-Learning Channel Autoencoder for Dynamic End-to-end Physical Layer Optimization". In *2025 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1-6). IEEE.
17. A. Bamdad, A. Owfi, and F. Afghah. "Adaptive Meta-learning-based Adversarial Training for Robust Automatic Modulation Classification". In WS25 ICC 2025 Workshop - NextG-WiSec

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