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Machine Learning Applications for Space Operations

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MACHINE LEARNING APPLICATIONS FOR SPACE OPERATIONS

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Project Summary

Due to the increasingly contested radio frequency (RF) environment, new approaches for satellite communications (SATCOM) interference detection and identification are needed. One approach is to apply machine-learning (ML) techniques, which can be applied on both the ground and space segments. This study focuses on exploring applications that can be supported by high-power computing, cloud-enabled services, and embedded ML hardware at the tactical edge. This study uses digitized RF transmissions to support the development of ML concepts for RF interference detection and identification. Due to the memory requirements for RF waveforms, the Cloud environment Azure was chosen to process the digitized waveforms and train the ML interference detectors. Azure shows promise in transitioning ML models to an austere environment (i.e., a ship) for processing large data sets. In this application, it was discovered that feedforward autoencoders can be used to quickly and correctly identify RF interference applied at various signal-to-noise ratios (SNRs). The statistic of corrupted signals may be classified to determine the specific type of interface that has been applied. Other ML architectures, such as long-short-term memory (LSTM) and convolutional neural networks (CNNs) are also applicable as they can process temporal features differently than an autoencoder network. Upon detection of jamming or signal degradation, it may be necessary to steer a SATCOM system to reestablish degraded and/or broken links. This aspect can be handled by performing a rapid spacecraft reorientation maneuver. The current state of practice involves developing appropriate maneuver on the ground for uplink and execution on board the vehicle. To establish autonomy of operation, a concept for on-orbit (edge) command generation using neural networks was demonstrated that can support event-driven and autonomous operations for communication applications that benefit the warfighter.

Keywords: *machine learning, radio frequency, RF, interference detection, space communications, on-orbit processing, tactical edge processing*

Background

Currently, RF interference detection for the space-to-ground link often requires extensive time-consuming site surveying to characterize the RF environment of the ground site, and these methods also require the use of spectrum analyzers on-site to visualize anomalies. Other figures of merit, such as SNR and bit error rate, are also used to assess the quality of the link. Current systems are labor-intensive because human operators are needed to evaluate frequency-use requests and interference reports. This bottleneck reduces command and control capability with respect to operational time for communications.

Statistical and ML methods have been explored for RF interference, most notably for wireless communications and GPS interference (Balaei & Dempster, 2009; Ganney & Ajib, 2020; Henarejos et al., 2019; Ujan et al., 2020). However, the literature for space-based communications—the focus of this study—is still limited. Data collected for known "clean" transmissions can be used to train the model, and the ML model can be easily adapted by performing a weight update when new types of interference are detected. This 'agility' can potentially provide a tactical advantage to the warfighter. In addition, the approach provides for autonomy that can be applied for efficient operations of large constellations.

Digitized RF transmissions were collected with commercial-off-the-shelf (COTS) software-defined radios (SDRs) that are used for educational purposes, with and without noise. The data was then used to develop an ML training environment with standard Python libraries for analyzing maritime communications. Two ML models, a dense autoencoder and an LSTM autoencoder, were trained on raw in-phase and quadrature RF data collected in a lab environment. A quadrature phase shift keying waveform in S-band was used in this study as a realistic signal for space-to-ground communication systems. Various SNRs were tested to represent strong, degraded, and denied links. Reconstruction error, the standard deviation of the mean-squared-error (MSE), and relative computing requirements were the primary figures of merit used to evaluate the effectiveness of the autoencoders to detect anomalous signals (Turdo, 2024).

Once interference has been detected, it should be mitigated. In the context of a SATCOM network, such mitigation may involve establishing a link with an alternative satellite that is not within a jamming footprint. To reconfigure the communications network quickly, it is necessary to execute rapid replanning and pointing of the spacecraft in a constellation. To support this aspect, fast reorientation trajectories may be used. Presently, this approach is done as part of a ground-based planning process (Karpenko et al., 2022). Machine learning and neural networks can be employed to enable in-situ trajectory optimization and maneuver generation autonomy. Specifically, several types of network architectures have been applied thus far, including recurrent LSTM neural networks and feedforward networks. Therefore, this approach shows promise for COMSAT architectures. In this study, we focus on extreme learning machines (Huang, 2006) that can be more easily deployed at the computational edge. Using extreme learning machines for on-orbit command generation can support event-driven and autonomous operations, which can potentially benefit maritime operators.

Findings and Conclusions

In this study, it was determined that feedforward autoencoders can be used to quickly and correctly identify RF interference applied at various SNRs. Because autoencoders are an unsupervised learning architecture that aim to reproduce a copy of the input signal at the network output, corrupted signals create an error on the output. The signature of the output errors can be statistically tied to the interference level and/or type. These statistics may be classified to determine the specific type of interface that has been applied. Other ML architectures, such as LSTM and CNN networks are also applicable as they can process temporal features differently than an autoencoder network.

Two autoencoder structures were studied: dense autoencoder and LSTM autoencoder. The dense autoencoder successfully detected the denied link but was not as effective in detecting the degraded link; however, the dense autoencoder has much lower computation requirements, making it very time efficient in both training the model and RF link analysis when compared to the LSTM autoencoder. The LSTM autoencoder was more sensitive to link degradation and thus performed better at detecting low-power anomalies in the RF signal. An MSE standard-deviation threshold was established successfully at four of the six data collection points for this method, compared to only one with the dense autoencoder; this threshold facilitated the filtering of false positives. These results show promise for communications operators who would have insights into a degraded signal, despite a functioning RF link (Turdo, 2024).

Degraded or broken links can be re-established by performing an optimized maneuver encoded in an ML model for rapid deployment at the edge. A key finding was that extreme learning machines can adequately characterize the trajectory database without the need for executing a conventional ML learning process. This result was established via simulations. The results can be leveraged to facilitate on-orbit autonomy in resource constrained compute environments. Alternatively, the results can be implemented in a Cloud-based scheme, wherein a centralized planning process both detects and classifies interference and then solves a resource allocation problem with autonomous maneuver design to reconfigure a satellite communications network.

Recommendations for Further Research

Future work includes applying the autoencoders to real-world data to assess the sensitivity of these models in an environment where there are slight changes in amplitude as it propagates through the atmosphere, as well as shifts in frequency as the satellite passes over a ground receiver, for example. The use of the Azure Cloud environment was successful in reducing the computation time, particularly as in-phase and quadrature data sets can be very large. The use of widely available software, such as Python, also enables the portability of this capability to austere environments (Turdo, 2024). This research has the potential to be expanded to a wide range of radio frequency applications, such as GPS (Global Positioning System) interference detection.

This research has also shown that utilizing machine-learning surrogates appears to be a viable approach for extending on-orbit operational autonomy. However, the current results have only been tested in simulations. It is, therefore, recommended that resources be made available to demonstrate the capability for radio frequency interference detection and autonomous on-orbit maneuvering to support communications constellation reconfiguration. This can be done inexpensively, by utilizing various path finding CubeSat missions that are presently operational or are being planned in the future. The lessons learned will help to inform and shape the evolution of these new concepts so that they may be applied in support of the warfighter.

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Acronyms

CNN	convolutional neural network
COTS	commercial-off-the-shelf
GPS	Global Positioning System
LSTM	long-short-term memory
ML	machine learning
MSE	mean-squared-error
RF	radio frequency
SATCOM	satellite communications
SDR	software-defined radio
SNR	signal-to-noise ratio