Space Object Identification, Discrimination, and Tracking

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ABSTRACT

The drastic rise in the number of objects in space and the proliferation of large constellations of commercial and government satellites is driving the need for rapid location, identification, discrimination, and attribution of non-cooperative space-borne objects. Traditionally, these needs have been addressed by two fundamental phenomenologies; Ground-Based Radar (GBR) systems and Electro-Optical (EO) sensors. This paper presents and highlights EO- and GBR-augmentation from passive Radio Frequency (RF), a powerful Space Domain Awareness (SDA) phenomenology. Passive RF provides important techniques for uniquely identifying and locating objects. Specific Emitter Identification (SEI) can occur when passive RF fingerprints are combined with Passive RF Ranging (PRFR) data.

1. INTRODUCTION

Numerous current and emerging needs exist to rapidly locate, identify, discriminate, and attribute non-cooperative space-borne objects. This paper presents a technique to fuse SEI-based RF fingerprints with Passive RF Ranging (PRFR) data as a means of uniquely identifying objects.

Traditional techniques utilize EO and radar sensors, each with their own limitations.

- Passive EO techniques may perform well during the night, but become ineffective during daylight or cloudy conditions, and are hampered by lightning strikes. EO sensors have trouble distinguishing objects of similar size (e.g., cubesat visual magnitudes are similar). Further, as seen with Space X Starlink, many satellites employ sunshades or are painted black as to not impact astronomers. These factors increase the difficulty to identify or track these objects with EO techniques.

- Radar is generally effective in all weather conditions, day or night, but has difficulty distinguishing between objects of similar size and shape (e.g., cubesat radar cross sections are very similar). Further, radars transmit high power RF, are expensive, and are therefore sparsely deployed.

- Radar and EO techniques may not clearly differentiate between closely spaced objects.

PRFR is an excellent augmenting phenomenology to EO and GBR as it performs well in all weather conditions, day or night and can uniquely identify active satellites of the same size, shape, and brightness, even when in close proximity.

The following sections overview PRFR and SEI. This paper concludes with discussions of their valuable fusion to the substantial benefit of the overall SDA community.

2. PASSIVE RF RANGING OVERVIEW

PRFR uses RF signals normally transmitted by a satellite to determine its position and velocity (i.e., state vectors). PRFR does not require coordination with the satellite owner, and can work with the satellite's usual beacon, telemetry, Command and Control (C2), and/or Satellite Communications (SATCOM) signals.

For accurate PRFR, the RF signal must be received by at least three ground antennas located at least several hundred miles apart. Ideally, the three antenna sites are positioned triangularly, and are separated by large latitudinal and longitudinal distance. This ensures that Difference of Arrival (DOA) measurements can be taken in both the in-track and cross-track directions of the satellite. This reduces the Orbit Determination (OD) errors in both directions. Fig. 1 shows the locations of the Kratos PRFR antenna sites in the Continental United States (CONUS). These antenna sites were used to collect the data for the examples in this paper.

Fig. 1. Kratos CONUS PRFR Sites

With PRFR, the RF signal from the satellite is digitized, time-tagged, and recorded at each antenna site. The recorded RF data is transferred to a central processing location where a Cross-Ambiguity Function (CAF) is performed. The CAF cross-correlates the RF signals with varying Time Difference of Arrival (TDOA) and Frequency Difference of Arrival (FDOA) values, returning the TDOA and FDOA values which produces the strongest correlation between the recorded RF signals. Fig. 2 is an example of a CAF result for satellite Anik-F1R (NORAD ID 28868) between two antenna sites.

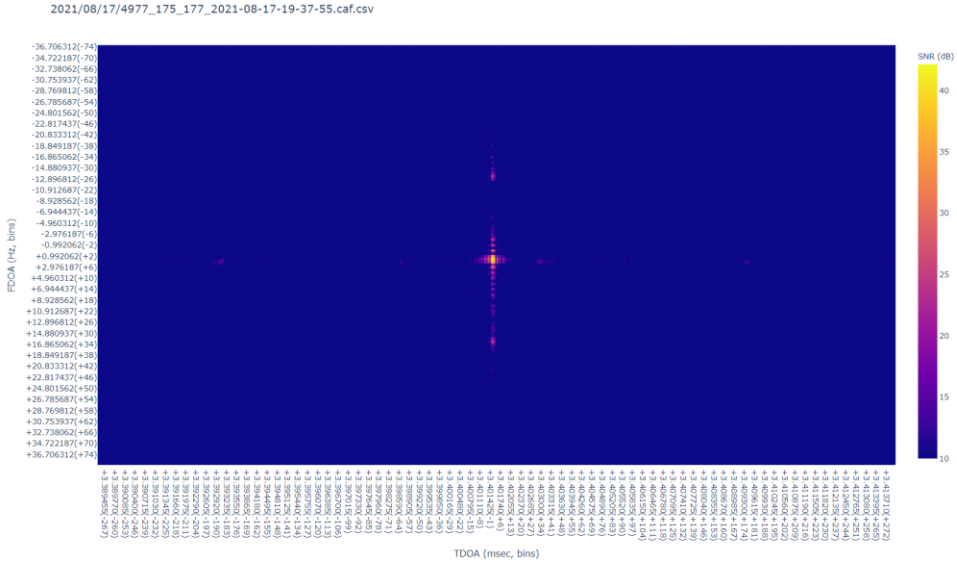

Fig. 2. Anik-F1R Cross Ambiguity Function

TDOA and FDOA values are the foundational measurements of PRFR. TDOA values indicate how much longer the RF signal took to arrive at one site relative to another site. This corresponds to the difference in distance from the satellite to each site. FDOA values indicate the difference in received Doppler shift between one site relative to another site. This corresponds to the difference in relative speed between the satellite and each site. Fig. 3 is an example of TDOA and FDOA measurements for satellite Anik-F1R. The signal's center frequency in this example was collected at 11960 MHz

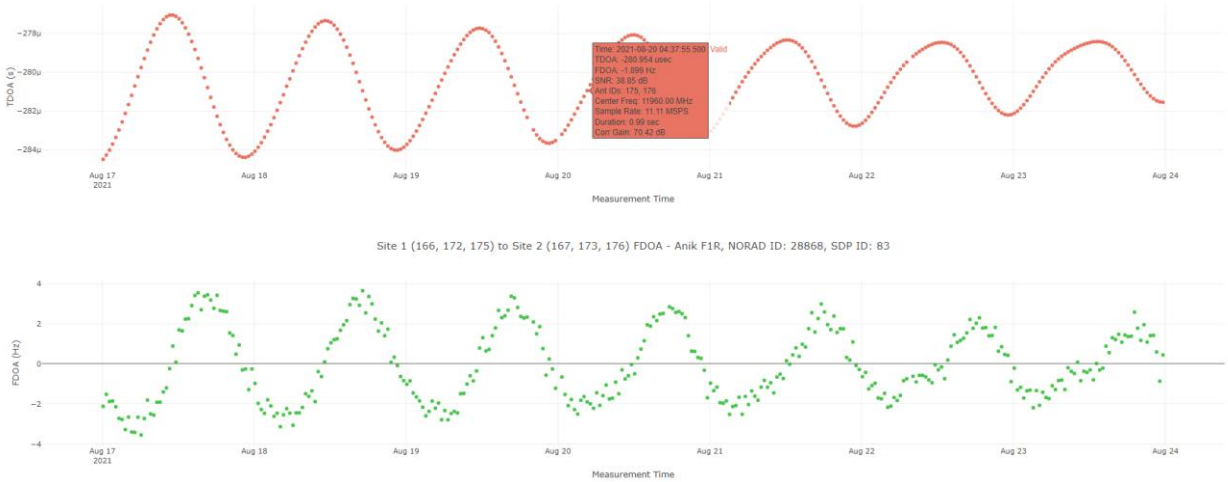

Fig. 3. Anik-F1R TDOA and FDOA Measurements

These TDOA and FDOA measurements are taken repeatedly over time, and between all antenna site pairs, and are then fed into a non-linear OD process. Both Batch Least-Squares (BLS) and Unscented Kalman Filter (UKF) approaches may be used. The OD process produces a state vector which describes the satellite's position and velocity at a specific time. Paired with a propagation model, state vectors are used to predict future positions of the satellite (i.e., ephemeris).

3. SPECIFIC EMITTER IDENTIFICATION OVERVIEW

As with PRFR, SEI uses RF signals normally transmitted by the satellite to uniquely identify transmitters. Similarly, SEI does not require coordination with the satellite owner, and can work with the satellite's usual beacon, telemetry, C2 and/or SATCOM signals.

SEI exploits the unintentional characteristics and perturbations of individual RF transmitters to uniquely identify transmitters by analyzing their transmitted signals. These transmitted signal "personalities" occur because of design and manufacturing differences between satellites, specifically in their digital-to-analog converters, frequency mixers, power amplifiers and other RF equipment. SEI generally requires only one ground site, although results can be improved with multiple sites. SEI implementation with RF Machine Learning (RFML) techniques is an area of active research, experimentation, and field trials with very encouraging results.

4. FUSION OF PASSIVE RF RANGING WITH SPECIFIC EMITTER IDENTIFICATION

The combination of PRFR with SEI augments existing SDA capabilities (e.g., EO and GBR techniques) and can improve overall SDA performance and resiliency. PRFR combined with SEI gives accurate identification, location, discrimination, and tracking of non-cooperative space-borne objects entirely via passive monitoring of their RF signals. The combined technique can provide positional and maneuver information and provide high-accuracy object discrimination in Rendezvous Proximity Operations (RPO) scenarios. Recently, ground-based radar and optical techniques have lost track of individual, closely spaced (< 1 km) objects (e.g., MEV-1 vehicle).

PRFR is mature and is based upon TDOA/FDOA processing from three or more spatially separated ground stations synchronized with a common Global Positioning System (GPS)-based timing reference. This technique is currently used at Kratos, and an example of actual, measured results are plotted in Fig. 4. Using the GPS-based Wide Area Augmentation System (WAAS) as the truth position, Fig. 4 shows the error (in meters) between the position result provided by Kratos Global Sensor Network (KGSN) PRFR and the WAAS-generated position. The results are plotted over time (in days). The positioning error is consistently less than 70 meters.

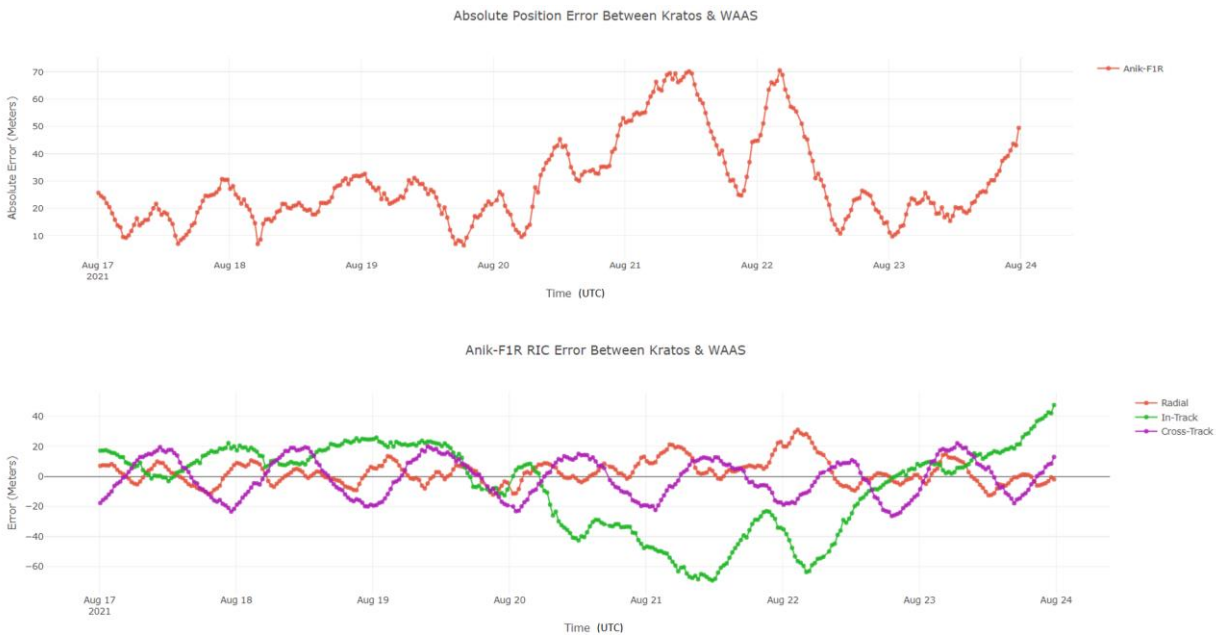

Fig. 4. Kratos PRFR State Vector Error

Neural Network (NN) detection and identification of RF fingerprints as an SEI technique, is the subject of significant active research, development, and testing as published in the open literature. As an example,

Fig. 5 depicts proof-of-concept results from a RFML effort conducted by the Hume Center for National Security and Technology at Virginia Tech University. It shows the gain offset separation (or, in other words "feature amplitude offset") needed between transmitters to achieve 80, 90, and 95% probabilities of correct identification of a specific transmitter.

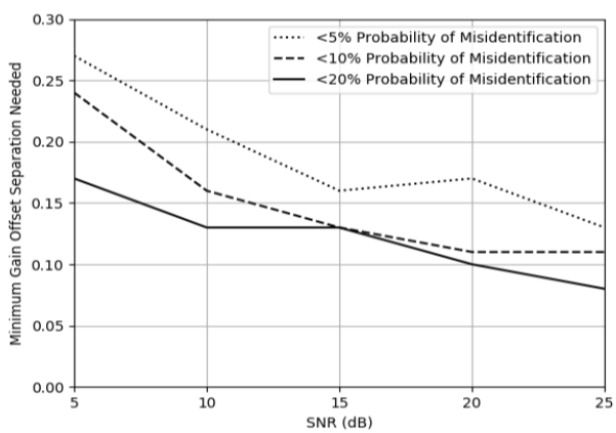

Fig. 5. Probability of Correct Identification of Transmitters [1]

Fig. 5 shows, in general, that the probability of correct identification improves as the fingerprint differences between transmitters increase (moving up the y-axis) and/or as the Signal-to-Noise ratio (SNR) increases (moving to the right on the x-axis). Although this is only one example, it is representative of today's SEI approaches, and it reveals the power of NNs to identify specific transmitters utilizing RF fingerprints. NN-based SEI is agnostic to signal modulation and doesn't require excessive over-sampling and dynamic range which are often required by the traditional expert-defined (e.g. human Subject Matter Expert (SME)) feature detection. Further, the results shown in Fig. 5 were obtained by feeding the NN a mere 1024 samples of raw I/Q samples.

Typically, NN performance is highly dependent upon exhaustive training with a representative emissions data set from the transmitters to be identified. This is potentially problematic when identifying non-cooperative transmitters, since there may be little data available. However, NN-based SEI capabilities can accommodate the identification of as-yet unseen/unknown transmitters for which the system has not been trained. To address this challenge, the process involves deciding when incoming fingerprints are sufficiently different from the existing set of reference/training data such that they indicate the presence of a new transmitter. Then, the approach trains to identify a statistically significant divergence in RF signature features from the existing reference sets.

NN-based RFML performance for SEI is often shown with confusion matrices, as in Fig. 6.

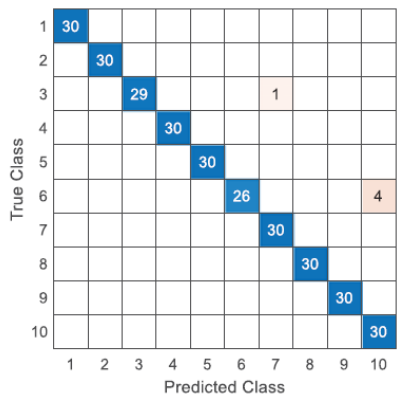

Fig. 6. Confusion Matrix of NN-based SEI Performance [2]

Confusion matrices help to visualize the performance of a machine learning classifier when the true transmitter classes are known. Perfect performance is achieved when the NN blindly classifies each transmitter correctly and is visualized by a single diagonal line across the matrix (e.g., the blue squares), with test count values in each cell. In this example, the NN-based performance outperformed the traditional SEI technique of expert feature analysis.

Specific Emitter Identification and Applicability to LEO Proliferation

The future of the space domain is expected to be characterized by the proliferation of large constellations of satellites, especially in Low Earth Orbit (LEO). The proliferated LEO scenario presents significant challenges to traditional optical and radar SDA tracking techniques. This has been seen recently with the SpaceX Starlink constellation. Astronomers have complained that the brightness of the Starlink satellites make it difficult to make observations. In response, SpaceX has applied experimental coatings and sunshades to make their satellites optically dimmer. This could result in traditional optical SDA sensors struggling to track these satellites.

Due to technology advances, CubeSats are being used advantageously in large constellations to reduce manufacturing cost and time, and to proliferate a common physical design. This hinders ground-based radars in uniquely distinguishing satellites because many satellites share a common radar cross section.

Both of these recent changes mean optical sensors and ground-based radars might struggle to uniquely identify satellites. As a result, cross tagging and identification failures will increase in traditional SDA systems. When traditional SDA capabilities are augmented with PRFR and SEI, the proliferated LEO environment of the future will be more manageable for active satellites.

PRFR can be used to track active objects as well as uniquely identify objects by their transmitter. This allows traditional SDA phenomenologies to focus more on debris, even as they continue their mission with active satellites. Uniquely identifying satellites by their own transmit capabilities allows the Department of Defense, Space Traffic Management, and Commercial providers such as Kratos to build and maintain space catalogs which can assist in notifying owners and operators of expected collisions.

Mapping Multiple Signals to a Single Satellite

Satellites flying multiple payloads are an example of the value of SEI and PRFR fusion. For example, Anik-F1R flies multiple C-band payloads and multiple Ku-band payloads. Each transponder in those bands exhibits different SEI characteristics allowing each transponder to be uniquely identified. Fig. 7 shows an example of a C-band transponder and its associated signals on Anik-F1R.

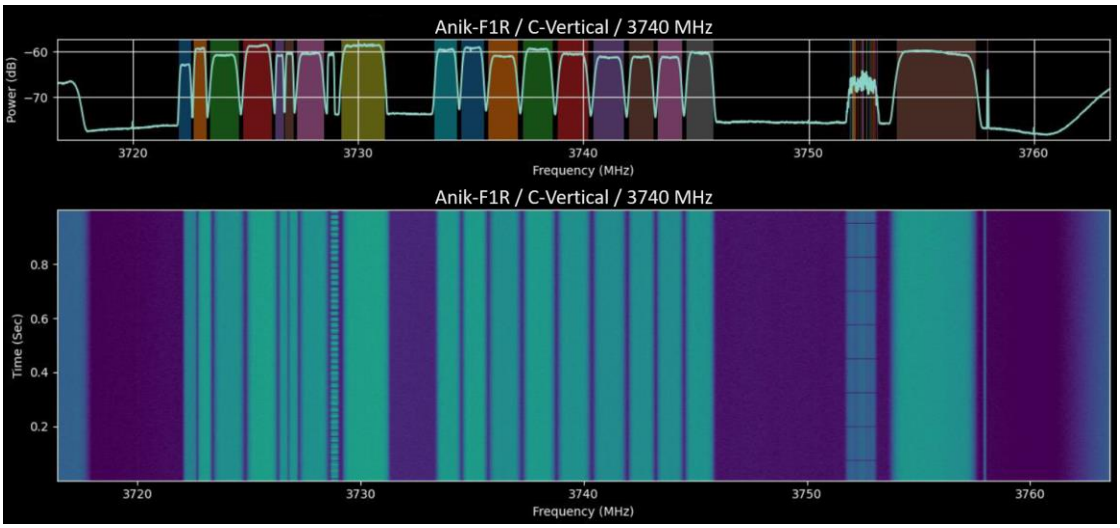

Fig. 7. Anik-F1R C-Band Transponder Frequency Scan

SEI processing on this C-band transponder gives it a unique identifier. PRFR can be used on each carrier to ensure each signal is coming from the same satellite and the same transponder. Fig. 8 shows an example of a Ku-band transponder and the associated signal on the transponder.

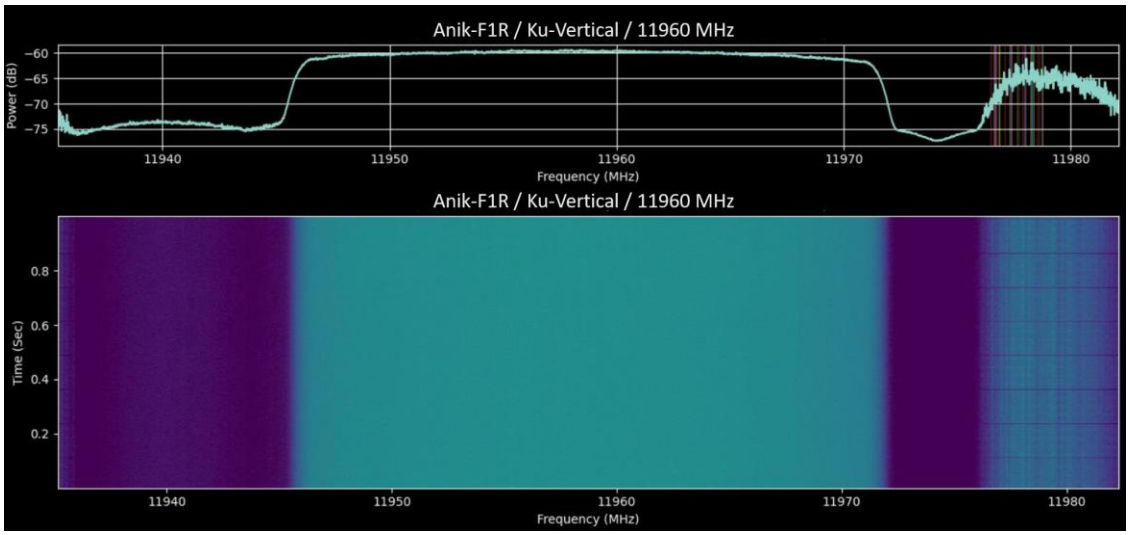

Fig. 8. Anik-F1R Ku-Band Transponder Frequency Scan

This specific signal is the same signal used for the TDOA/FDOA measurements seen in Fig. 3 and Fig. 4. PRFR can be used to locate the position of this signal, and SEI can be used to catalog the new transponder. Once the positions are confirmed identical between the C-band transponder and the Ku-band transponder, it can be concluded that the transponders are on the same satellite. This information is useful when attributing a particular satellite.

SEI and PRFR are techniques that allow Kratos to construct databases that uniquely relate satellites, transmitters and signals. This helps with satellite identification and tracking, especially in closely spaced object scenarios in the GEO belt.

5. CONCLUSION

The underlying PRFR and RFML-based SEI technologies are proven and mature. A valuable synergy is achieved in the integration of these two technologies to empower detection, identification, discrimination, and location of non-cooperative space-borne transmitters. This is of particular value when vehicles fly in clusters, are in Closely Spaced Operations (CSO) scenarios, or use common architectures like a CubeSat. Specifically, these capabilities enable the SDA community to uniquely identify individual satellites within large constellations such as SpaceX Starlink, OneWeb, Amazon, Telesat, and Guo Wang. PRFR and SEI improve space object position knowledge, preserving safety of flight for all objects. Kratos deploys some of these capabilities today through an existing network of commercially accessible sensors, the Kratos Global Sensor Network (KGSN), to passively range objects and implement fusion with SEI.

6. REFERENCES

[1] J.M. McGinthy, L.J. Wong, A.J. Michaels. Groundwork for Neural Network-Based Specific Emitter Identification Authentication for IoT. *IEEE Internet of Things Journal*, Vol. 6, No. 4, August 2019.

[2] Y. Lin, J. Jia, S. Wang, B. Ge, S. Mao. Wireless Device Identification Based on Radio Frequency Fingerprint Features. *IEEE Xplore*.

7. ABBREVIATIONS and ACRONYMS

The following abbreviations and acronyms are used in this paper.

Table 1. Abbreviations and Acronyms

Abbreviation / Acronym	Meaning
BLS	Batch Least-Squares
C2	Command and Control
CAF	Cross-Ambiguity Function
CONUS	Continental United States
CSO	Closely Spaced Operations
dB	Decibel
DOA	Difference of Arrival
EO	Electro-Optical
FDOA	Frequency Difference of Arrival
GBR	Ground-based RADAR
GPS	Global Positioning System
ID	Identifier
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
I/Q	In-Phase / Quadrature-Phase
KGSN	Kratos Global Sensor Network
LEO	Low Earth Orbit
MEV	Mission Extension Vehicle
NN	Neural Network
NORAD	North American Aerospace Defense Command
OD	Orbit Determination
POL	Pattern of Life
PRFR	Passive RF Ranging
RADAR	Radio Detection and Ranging
RF	Radio Frequency
RFML	RF Machine Learning
RIC	Radial, In-Track, Cross-Track
RPO	Rendezvous Proximity Operations
S	Seconds
SATCOM	Satellite Communications
SDA	Space Domain Awareness
Sec	Seconds
SEI	Specific Emitter Identification
SME	Subject Matter Expert
SNR	Signal to Noise Ratio
TDOA	Time Difference of Arrival
µ	Microseconds
UKF	Unscented Kalman Filter
UTC	Universal Coordinated Time
WAAS	Wide Area Augmentation System